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Marian Rizov
The Institute for International Integration Studies
Trinity College, Dublin

Patrick Paul Walsh
Department of Economics
Trinity College, Dublin
The Institute for International Integration Studies
Trinity College, Dublin

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MARIAN RIZOV

IIIS, THE SUTHERLAND CENTRE,
TRINITY COLLEGE DUBLIN,
DUBLIN 2, IRELAND.
EMAIL: RIZOVM@TCD.IE
TELEPHONE: 00-353-16083207

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PATRICK PAUL WALSH' §

IIIS & DEPARTMENT OF ECONOMICS,
TRINITY COLLEGE DUBLIN,
DUBLIN 2, IRELAND.
EMAIL: PPWALSH@TCD.IE
TELEPHONE: 00-353-16082326

Abstract

We estimate productivity dynamics within 4-digit manufacturing industries, using FAME data on UK Companies, from 1994 to 2003. We extend the algorithm in Olley and Pakes (1996) to allow for a selection bias driven by the Melitz (2003) effect (high productivity types selecting to exporting) to get more consistent and unbiased estimates of the parameters of the production function. We demonstrate a link between trade orientation and productivity within industries that is driven by selection, not by learning. Hence aggregate productivity is driven by market share reallocations amongst 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 focus of this paper is to outline a methodology that estimates the parameters of a production function but allows for the unobservable to be affected by a discrete and endogenous trade orientation choice by companies within 4-digit industries, among other factors. This is achieved by adapting an algorithm developed in Olley and Pakes (1996) and applying it to an unbalanced panel of exporting and non-exporting companies within 4-digit industries in the manufacturing sector of the UK economy with annual observations for the period 1994 -2003.

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. As a result, we estimate production functions (productivity) for sub-samples of exporting and non-exporting companies within 4-digit industries allowing for endogenous selection using trade orientation information at the company level. The purpose of this paper is to estimate productivity in a way that allows us to understand the nature of productivity differences between exporting and non-exporting companys and document contributions to aggregate productivity.

Our approach brings together two strands of literature on productivity and exporting. These are summarised nicely in Bernard and Jensen (1999 and 2001). In the former paper they estimate total factor productivity using Olley and Pakes (1996) as a first step to solve for producer-and-time specific approximations of productivity, ω. They proceed to link ω to company exporting and aggregate productivity.[1] It is our view that testing for a relationship between exporting and the unobservable, 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 guides us. Melitz (2003) provides a model of selection with theoretical foundations. This model employs sunk costs associated with exporting that lead to only high productivity companies selecting to exporting. Hence selection generates productivity differences between exporters and non-exporters, and movements in aggregate productivity induced solely by market share reallocations and not by improvements in productivity at the company level.[2] Roberts and Tybout (1997) for Colombia, Bernard and Jensen (2001) for the US, and Bernard and Wagner (2001) for Germany, document selection to exporting regressions and estimate that the magnitude of sunk export market entry costs is important enough to allow only high productivity types to export and generate persistence in company level export market participation.

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[1] Using available output and input measures many studies, some using growth accounting and others production estimates, first solve for approximations of productivity and then correlate productivity estimates with whether a company exports, amongst other factors. Pavcnik (2002), Lopez-Cordova (2002) and Fernandes (2001) for example, Olley and Pakes (1996) to approximate ω in the first stage and correlate with trade in a second step.

[2] We define "market share reallocation" as a process where high productivity types remain in the industry and get bigger by exporting, while low productivity types exit or get smaller as a non-exporter.

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. This would ensure that the productivity backed out of the production function would reflect co-efficient's on labour and capital, amongst other observables, that were estimated allowing for selection to trade bias in the unobservable. He uses a system GMM parameter approach in his paper. As demonstrated in De Loecker (2004) and McGoldrick and Walsh (2004) one can adapt the algorithm developed in Olley and Pakes (1996) to allow for an additional selection rule, alongside other selection rules and investment dynamics of companies, given the observable state variables, to control more effectively for the omitted unobservable (productivity) using non-parametric techniques. This is the semi-parametric alternative.

De Loecker (2004) and Van Biesebroeck (2003) after allowing for selection to trade bias in the unobservable argue that learning by doing (productivity improvements in companys induced by exporting) was still present in their ex-post analysis of productivity in Slovenia and Sub-Saharan Africa, respectively. While this is an appealing result, particularly during transition and early industrial development, this creates the following methodological problem. If one believes that learning-by-doing in companies is present in the unobservable, then one should also control for this when estimating the parameters of the production function. Otherwise, we are back to the possibility of having productivity estimates that may give us learning inferences in ex-post analysis when in reality we just have a misinterpretation of noise.[3] Our approach is to impose the selection model as the true model and hope for ex-post validation. If we find learning, then we need another model of the unobservable and re-estimate.

The motivation for choosing an adapted version of the Olley and Pakes (1996) algorithm is to allow for productivity to be dynamic, while controlling for simultaneity and selection biases. The Olley and Pakes (1996) approach postulates a structural model of the unobservable, which suggests that selection rules and investment dynamics of enterprises, given the observable state variables, should allow one to control effectively for the omitted unobservable (productivity) using a non-parametric technique.[4] This allows one to get consistent estimates of the co-efficient's on labour and capital, amongst other observables. A consistent productivity index for each enterprise can then

[3] Another serious issue, if we believe configurations of productivity types have evolved as in Hopenhayn (1992) in industry evolution, or resulted from the nature of sunk costs in industry evolution, as in Sutton (1998), the distribution of productivity types is stable in equilibrium. It is then natural to think of productivity type as a state variable in mature industries. This is important for the Olley and Pakes (1996) estimation routine. It is clear that productivity type may be a choice variable during early development and in an industry in transition. This makes the application of Olley and Pakes (1996) questionable and allowing for learning by doing non-trivial. Our approach is to take the distribution of productivity types as a given, an outcome of industry evolution, and identify selection into exporting on a cross-section of productivity types and other company characteristics.

[4] Even though Olley and Pakes (1996) motivate their structural (theoretical model) of the unobservable with Ericson and Pakes (1995), which assumes the existence of Markov perfect Nash equilibrium over-time, the econometric technique is operational when investment sequences and selection rules are weakly rational, driven in some part by observable and unobservable state variables.

be backed out as a residual in the production function. In addition to allowing for a selection bias due to the exit of companies, as in Olley and Pakes (1996), another bias comes from selection into exporting that creates unbalanced panels of companies in exporting and non-exporting states, a discrete choice, whose adoption dates are company specific and depend on the productivity, among other factors. The idea of this paper is to control for the Melitz (2003) selection mechanism in the modelling of the unobservable, amongst other factors, as we estimate the parameters of the production function. Thus, we make a contribution to the efficiency and trade debate, adding evidence from the fifth largest exporter in the world.[5]

Adapting the algorithm in Olley and Pakes (1996) to allow for an additional selection rule, allows us to get more consistent estimates of the β's on labour and capital, amongst other observables and hence one can back out better estimates of the unobservable, ω. As a counterfactual, we show that ignoring trade bias in the structural algorithm of Olley and Pakes (1996) leads to spurious measures of productivity that are hard to correlate with trade orientation ex-post. While other measures do not, our 4-step Olley and Pakes (1996) estimates show clear differences in the mean and variance of productivity over-time by trade orientation.[6] We also show, using ex-post regressions, that the correlation between exporting status and estimates of the unobservable, ω, is spurious when using OLS, GLS and Olley and Pakes (1996) estimators that do not allow for trade bias. In addition, we verify that investment dynamics, exit and trade orientation choices are indeed driven significantly by our 4-step estimates of productivity.

Having consistent estimates of productivity we investigate the relative merits of the selection and learning hypotheses. We find evidence supporting the self-selection of more

[5] In summary this literature 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; Pavnic (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. The learning hypothesis receives somewhat less support, however. Castellini (2001) reports some evidence suggesting that the productivity of exporting companies may increase with increases in export intensity. For Chinese companys, 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.

[6] The methodology to allow for selection biases resulting from company level decisions in the estimation of productivity can easily be applied to other areas of economic interest, such as evaluating productivity across groups defined by state versus private ownership and domestic versus foreign outsourcing of intermediate inputs. Amiti and Konings (2005) focus on status of imports in terms of final versus intermediate goods. Another literature that is relevant considers the effect of imported versus indigenous input status on productivity (Feenstra, Markusen, and Zeile, 1992; Kasahara and Rodriguez, 2004). The tendency here is to estimate total factor productivity (TFP), without controlling for endogenous selection to a status, and in a second step, TFP is then linked to a particular status. Clearly, it is better to allow for endogenous selection in the estimation of TFP in the first place. Otherwise, the TFP backed out will be from a badly specified production function and could have a spurious relationship with other variables.

productive companys into the export market. As a result, we show that improvements in aggregate productivity are driven by productive companies getting bigger rather than from changes in productivity. Melitz (2003) theoretically describes and analyzes a transmission channel for the impact of trade on industry structure and performance that works through intra-industry reallocations across heterogeneous companies. Trade induced reallocations towards more efficient companies explain why trade generates aggregate productivity gains without necessarily improving the productive efficiency of individual companies.

Katayama Lu, and Tybout (2003) levy a critic of company level productivity studies. Production functions should be a mapping of data on inputs and outputs. Normally, studies use revenues and expenditure data. As in this study most use industry level deflators for output, raw material and capital assets to get back the quantity data needed. In differentiated product industries it is clear that inputs and outputs can be priced differently even within narrowly defined industries. Hence the residual may reflect errors in the measurement of inputs and output and not just efficiency. This is more serious when one realizes that pricing in imperfect competition is endogenous. If one ignores this problem we could end up with poor estimates of the parameters, a bad measure of productivity driving spurious correlations with others variables. Their solution is to employ a structural model of demand and supply, based on Berry (1994), using revenue and expenditure data, to estimate performance and link to such issues as trade. We feel that our selection rule into exporting may also depend on market power, among other factors. For any given productivity, more profits from higher pricing will induce participation in exporting. We use size variables to proxy for market power in our selection equation to exporting. One implication of controlling for this type of selection in the unobservable is that it may control for an exchange rate adjusted pricing gap between exporters and non-exporters in their use of inputs and outputs. There is a clear and persistent gap in the real effective exchange rate at the macroeconomic level and it is likely that this is also true within 4-digit industries. Clearly, the discrete nature of the exporting decision would not allow for movements in the real effective exchange rate over-time within 4-digit industries but this is one reason why we estimate a production function for exporting and non-exporting sub-samples within each 4-digit industry, allowing time dummies to control for changes in the real effective exchange rate movements, among other factors.

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 outlined in sections IV. In section V we undertake an analysis of learning from exporting versus state dependence in company level productivity within industries. In section VI we undertake our analysis of aggregate productivity and outline our conclusions in Section VII.

II. THE FAME DATA

According to Bureau van Dijk, FAME is the most comprehensive database of UK companies available, offering access to all companies filing at the Companies House in the UK.[7] Information available on FAME includes detailed financial statements, ownership structure, activity description, direct exports, various financial ratios and credit scores. 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.

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 plants 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 are heterogeneous in whether they export, they also differ substantially in various crude measures of productivity. Figure 2a plots the distribution across

[7] 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.

companies of value added per worker (segregating exporters from non-exporters) relative to the overall mean. Similarly, Figure 2b 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 bypass 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 plants 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 and to document the TFP gaps and 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 (listed in Appendix I), 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 terms of the smallest estimated sample, where the Olley-Pakes four stage 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.[8] The detailed definitions of regression variables are as follow: *Value added* is total sales adjusted for changes in

[8] 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. This empirical evidence is consistent with the discussion in footnote 3. We threat exporting as a fixed effect. We mark a company as an exporter if we observe exporting in any time period in the data. Allows for pre-selection effects.

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 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 the productivity variable is not measured directly 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 it 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 is 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 trade bias in the production function estimates and lead to inconsistent estimates of production function parameters. Our purpose is to incorporate the impact of trade in the algorithm for estimating the parameters of the production function. As shown by Melitz (2003), when there are no additional costs associated with trade, trade provides the same opportunities to an open economy as would an increase in country size in a closed economy. An increase in country size has no effect on company level outcomes. This impact is identical to the one described by Krugman (1980) with representative companies, although companies are not affected by the transition to trade, consumers enjoy welfare gains driven by the increase in product variety.

However, there is mounting evidence that companies wishing to export not only face per-unit costs (such as transport costs and tariffs), but also - critically - face some fixed costs that do not vary with export volume (Melitz, 2003). Bernard and Jensen (1999), Clerides, Lach and Tybout (1998) and Roberts and Tybout (1997) all introduce a fixed export cost into the theoretical sections of their work in order to explain the self-selection of companies into the export market.[9] Furthermore, Melitz (2003) assumes that a company that wishes to export must make an initial fixed investment, but that this investment decision occurs after the company's productivity is revealed. The strong and robust empirical correlations at the company level between export status and productivity suggest that the export market entry decision occurs after the company gains knowledge of its productivity. This would create selection trade bias in the production function estimates and lead to inconsistent estimates of production function parameters. We allow for this non-parametrically (no imposed functional form or distributional assumptions) in our estimation procedure.

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

$$y_{ijt} = \beta_0 + \beta_a a_{ijt} + \beta_k k_{ijt} + \beta_l l_{ijt} + \omega_{ijt} + \eta_{ijt} \qquad (1)$$

Thus, the log of company *i's* in industry *j's* 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_{it} is correlated with them. For labour the readily adjusted 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 productivity would be needed to select into exporting for higher capital stocks. Omitted

[9] The fixed export costs may vary in their nature: A company must find and inform foreign buyers about its product. It must then research the foreign regulatory environment and adapt its product to ensure that it conforms to foreign standards (which include testing, packaging, and labelling requirements). An exporting company must also set up new distribution channels in the foreign country and conform to all the shipping rules specified by the foreign customs agency. Although some of these costs cannot be avoided, others are often manipulated by governments in order to erect non-tariff barriers to trade. Regardless of their origin, these costs are most appropriately modelled as independent of the company's export volume decision and they must be sunk prior to entry into the export market.

productivity type will lead to a bias in the estimate of the capital coefficient. Other factors, such as higher mark-ups in export markets, could lead to selection, for any given sunk costs or productivity type. Hence, it will be important to control for additional factors in the selection equation. Similar arguments for the exit decision are outlined in Olley and Pakes (1996).

Next we outline our *four-step estimation procedure*. We assume that investment sequences, i_{ijt}, chase performance to some 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}. Assume that $i_{ijt} = h_{ijt}(\omega_{ijt}, a_{ijt}, k_{ijt})$ and more importantly that this function is invertible and differentiable such that $\omega_{ijt} = h_{ijt}(i_{ijt}, a_{ijt}, k_{ijt})$. Equation (1) can now 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. We use bootstrapping methods to recover the correct standard errors. The approximation of the unknown function with Kernel estimators has proven to generate similar results. The estimation of the return to labour in the production function above can be extended to control for selection biases. 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:

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

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

To obtain unbiased estimates of β_l, a partially linear, semi-parametric regression model is employed allowing for both selection biases. One can 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 our β_a and β_k using a non-linear least squares estimator:

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

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 Markov process and use lag one period 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.

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 $TFP_{ijt} = y_{ijt} - \beta_l\, l_{ijt} - \beta_k\, k_{ijt}$. We estimate what we feel are the most consistent and reliable *β's.* This will allow us to make inferences on the productivity differences between exporting and non-exporting companies as well as document their contributions to aggregate productivity.

IV. Estimation Results

In Table 3 we report a weighted average, using value added as weight, of the estimated coefficients from the 4-digit regressions outlined in Appendix I. We run a separate regression for the top 46 4-digit industries, or 82 regressions if we run regressions on exporting and non-exporting sub-samples within each 4-digit industry. First, 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 decision to stay 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 smaller as we control for simultaneity (2-step), the 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 gets bigger as we incorporate a richer model of the unobservable.

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 at the end of section III, includes the regression error by company. If we take away the regression errors we are left with the pure deterministic part of *TFP* - 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 estimated gap between exporters and non-exporters is highest 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.

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 residuals. 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 are graphed with and without regression residuals. 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 residual.

Clearly, allowing the co-efficient's to vary across trade orientation 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)).

Next, we summarize the Olley-Pakes 4-step 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.

We wish to show that omitting the selection process that determines market orientation of outputs from the structural algorithm of Olley and Pakes (1996) leads to spurious measures of productivity that are hard 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). Even though we do not agree with the causality, we show, using ex-post regressions at the 4-digit level, that the correlation between exporting status and estimates of the unobservable, *TFP*, is spurious when using OLS, GLS and Olley & Pakes estimators that do not allow for trade orientation in the estimation of the parameter of the production function. 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 productivity (results are weighted averages over the top 46 4-digit industries). In Table 4(b) we net out the regression error from the estimate of *TFP* and include it as an explanatory variable. The correlation of ω with exporting only survives when we have a rich deterministic model of *TFP*. This demonstrates that the inferences made using OLS, GLS and Olley-Pakes estimators not allowing for trade in the estimation of *TFP* are wrong. In addition, we verify that trade and investment choices are indeed driven significantly by our 4-step estimates of productivity. The results are outlined in Tables 5 and 6 for exporting and investment, respectively.

V. SELECTION VERSUS LEARNING

An alternative way of summarizing the movement in the company productivity distributions is to summarize the quartiles of each cross-sectional distribution. Table 7 reports the 25^{th}, 50^{th}, and 75^{th} percentiles for each of the eleven groups of 2-digit manufacturing industries in each of the five reported years (1994, 1996, 1998, 2000, 2002). Table 7 indicates that there has not been a substantial shift in the productivity distributions over time and the observed minimal shifts are not systematically related to export status. These shifts do not seem to follow a particular pattern and the magnitude of the shifts is by and large similar across exporters and non-exporters. Two industries, precision instruments (SIC 33) and transportation equipment (SIC 34, 35), are even characterized by a higher productivity of the median non-exporting company compared with the median exporting company. Productivity growth for the industry groups analyzed ranges, for the decade, between –9% and 42% for exporters and between –4% and 39% for non-exporters. The productivity growth for total manufacturing is 10% for exporters and 17% for non-exporters, suggesting that there is no evidence in support of the "learning-by-exporting" hypothesis. Only one industry group, basic and fabricated metals (SIC 27, 28), shows a decline in productivity, both for exporters and non-exporters, with the productivity of the median company falling by 1% and 4%, respectively over the decade. Other industry groups with declining productivity are publishing and printing (SIC 22) and transportation equipment (SIC 34, 35) but only for exporting companies. In the majority of cases, the rightward shift of the distribution is not accompanied by a significant change in the shape of the distribution from one cross-section year to the next. In particular, there is no evidence of a significant narrowing of the cross-sectional distributions over time for most of the industries. An exception is the electrical machinery group of industries (SIC 30, 31, 32) where the distribution has tightened substantially over the decade for the sample of exporters. The interquartile range (IQR) does fall over time for the most industry groups or remains almost unchanged. Most of the narrowing of the IQR comes from increase of the 25^{th} percentile. For example, the 25th percentile increased approximately by 17% over the decade while the 75^{th} percentile raised only by 4% when the total manufacturing sample of exporters is considered; the respective figures for the non-exporters are 11% and 8%, respectively. This indicates that it is a reduction in the mass of low productivity companies that generates the narrowing of productivity differentials in manufacturing, and the same holds true for the specific industries as well. Industries for which it is not the case are pulp and paper (SIC 21) and non-electrical machinery (SIC 29) as the increase in IQR is specific to non-exporters. In these cases the 75^{th} percentile increased more rapidly than the 25^{th} percentile, indicating that an increase in the mass of high productivity companies resulted in the increased dispersion.

The comparison of the productivity distributions across the years indicates that modest productivity increase is observed across most companies, both exporters and non-exporters. What the comparison cannot reveal, however, is the movement of individual companies through the distributions over time. The rightward shift in the distribution could reflect, at one extreme, the productivity growth for all companies at approximately the same rate, or at the other extreme, no productivity growth by any company but rather the exit of all companies in the low productivity tail of the distribution and their replacement by a cohort of new higher productivity companies. The movements of the productivity distributions also cannot reveal the change in industry-level productivity, which is a size-weighted average of the company productivities, since the distributions do not take into account differences in the size of the companies. If the size distribution of companies is quite skewed, as is true in most manufacturing industries, then movements of output or the reallocation of market shares among companies with different productivity levels, can have an important impact on industry-level productivity change.

For this reason, in Figure 5 the distribution of our estimates of productivity in the initial and final year of a balanced panel of companies across exporting and non-exporting status are compared, by graphing the log distributions computed from the 4-step Olley-Pakes algorithm. Productivity measures presented in Figure 5 are computed with and without regression errors, respectively. We see that the distributions are remarkably stable over this period. In Table 8 this assertion is confirmed by a simple regression on the balanced panel used. Using the 4-step Olley-Pakes estimate of productivity, without the regression error, we model productivity growth to depend on age, capital size, exporting status, regression error, amongst other factors. We see that exporting status does not explain growth. Random events have the most significant impact while initial productivity levels persist in that the better types grew a little more, but only marginally. This finding confirms the outcome in Figure 5. Overall we see persistence in company level productivity and stable productivity distributions within industries over time.

How did aggregate productivity grow in the UK? Micro-data studies such as Disney, Haskel, and Heden (2003) and Barnes and Haskel (2000; 2001) indicate that the reallocation of market shares and specifically, 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 the next section we confirm that market share expansion in efficient companies drives aggregate productivity, rather than productivity improvements within companies. In addition, we explore the role of trade orientation in the market share reallocation.

VI. AGGREGATE PRODUCTIVITY

In 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 6. 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; Dixon and Thirlwall, 1975). In this section 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:

$$P_t = \sum_i s_{it} \omega_{it} \tag{2}$$

where ω_{it} is company productivity as defined in previous sections and s_{it} is the value of company i 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 2 can be rewritten as:

$$P_t = \bar{P} + \sum_i \Delta s_{it} \Delta \omega_{it} \tag{3}$$

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 3 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 9 reports the aggregate productivity level for each of the nine industries in five cross-section years (1994, 1996, 1998, 2000, 2002). In addition, the decomposition according to equation 3 is reported as the covariance term is calculated separately for exporters and non-exporters, 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 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 term indicates that shifts in market share reallocations rather than the productivity distribution are the main source of industry productivity growth.

VII. CONCLUSION

We outline a methodology that estimates 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 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 that is driven by selection and not by learning. As a result, we show that recent improvements in aggregate productivity 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 (Helpman and Krugman, 1985; Krugman, 1994; Helpman, Melitz, and Yeaple, 2004).

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Figure 1: Industry exporting intensity

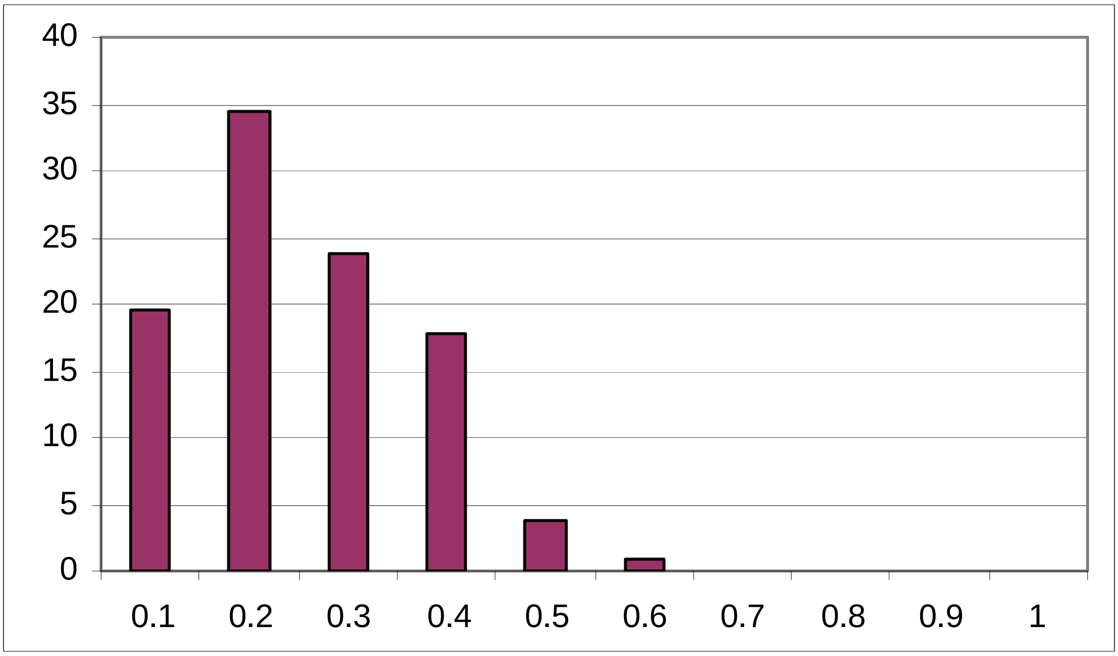


Figure 2(a): Ratio of company labour productivity to overall mean

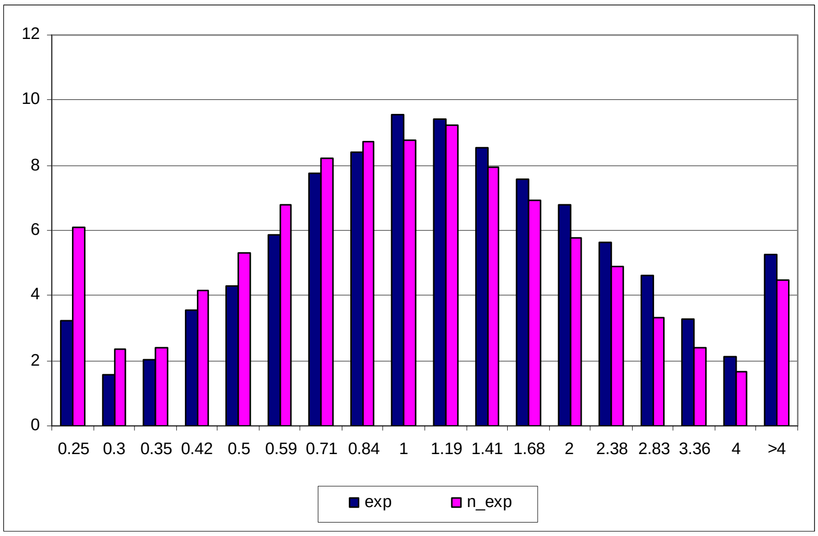


Figure 2(b): Ratio of company labour productivity to 4-digit industry mean

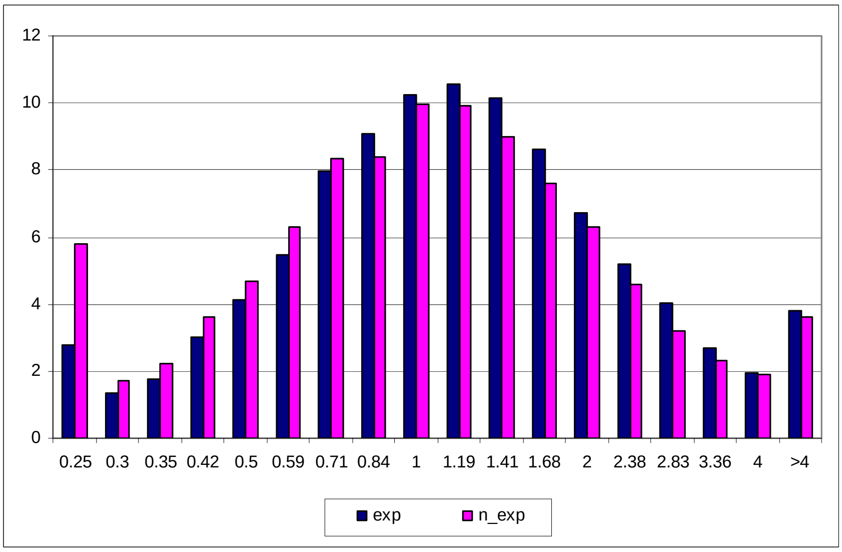
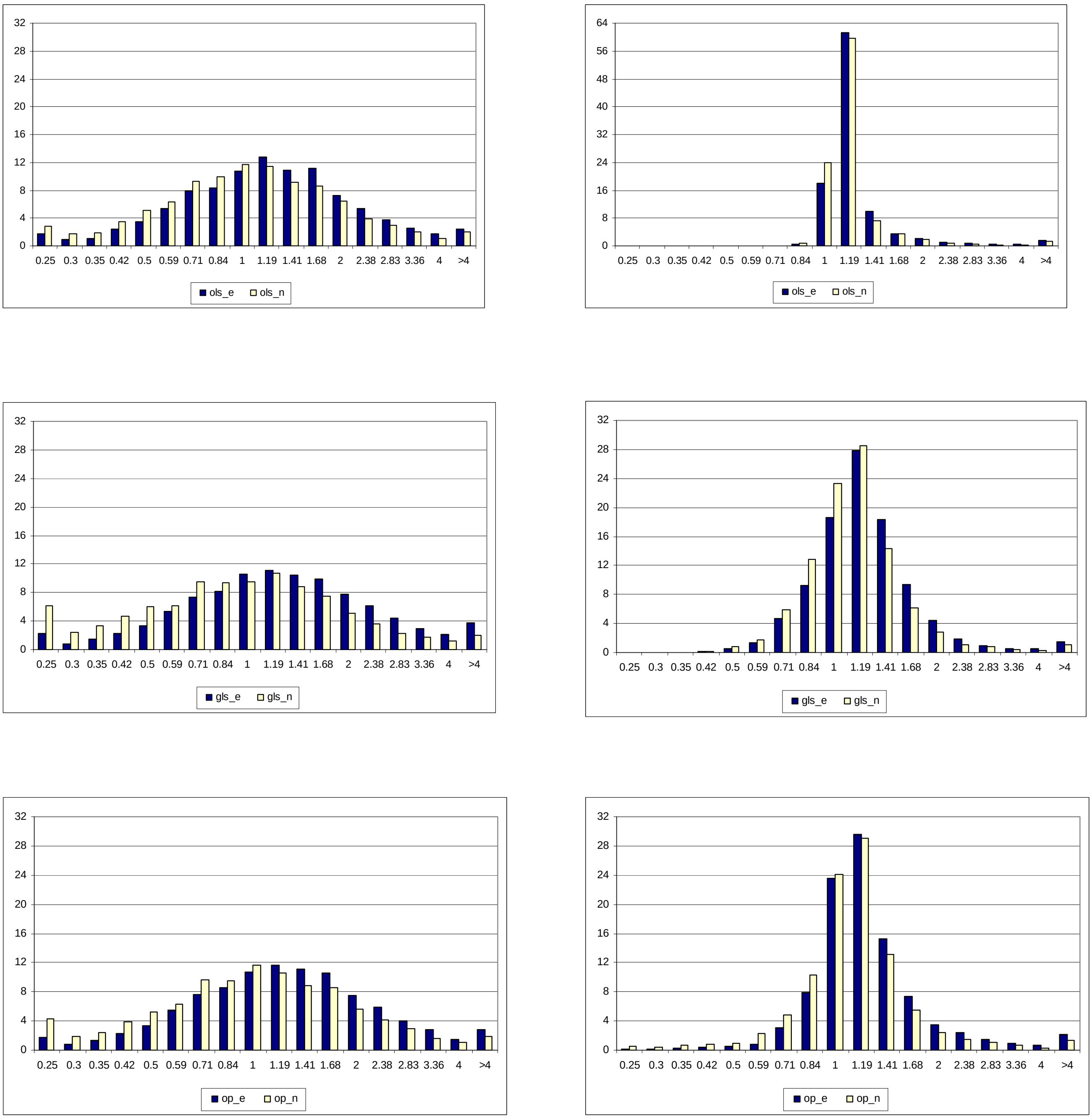


Figure 3(a): Comparing productivity of exporters and non-exporters

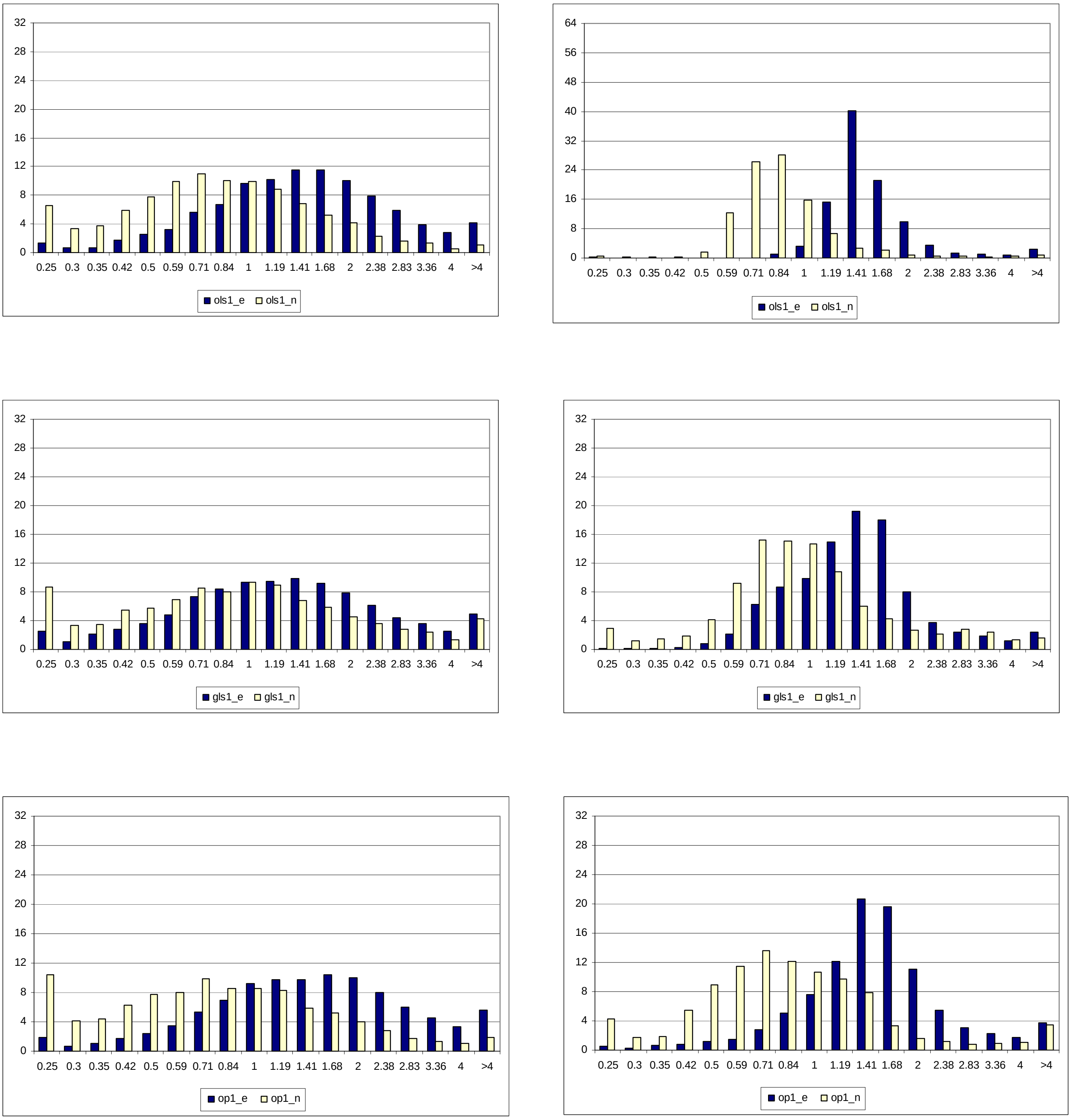
Productivity measure (deviation form 4-digit industry mean) calculated using OLS, GLS_fe, and Olley-Pakes 2-step coefficient estimates, with and without the first-stage errors



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

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

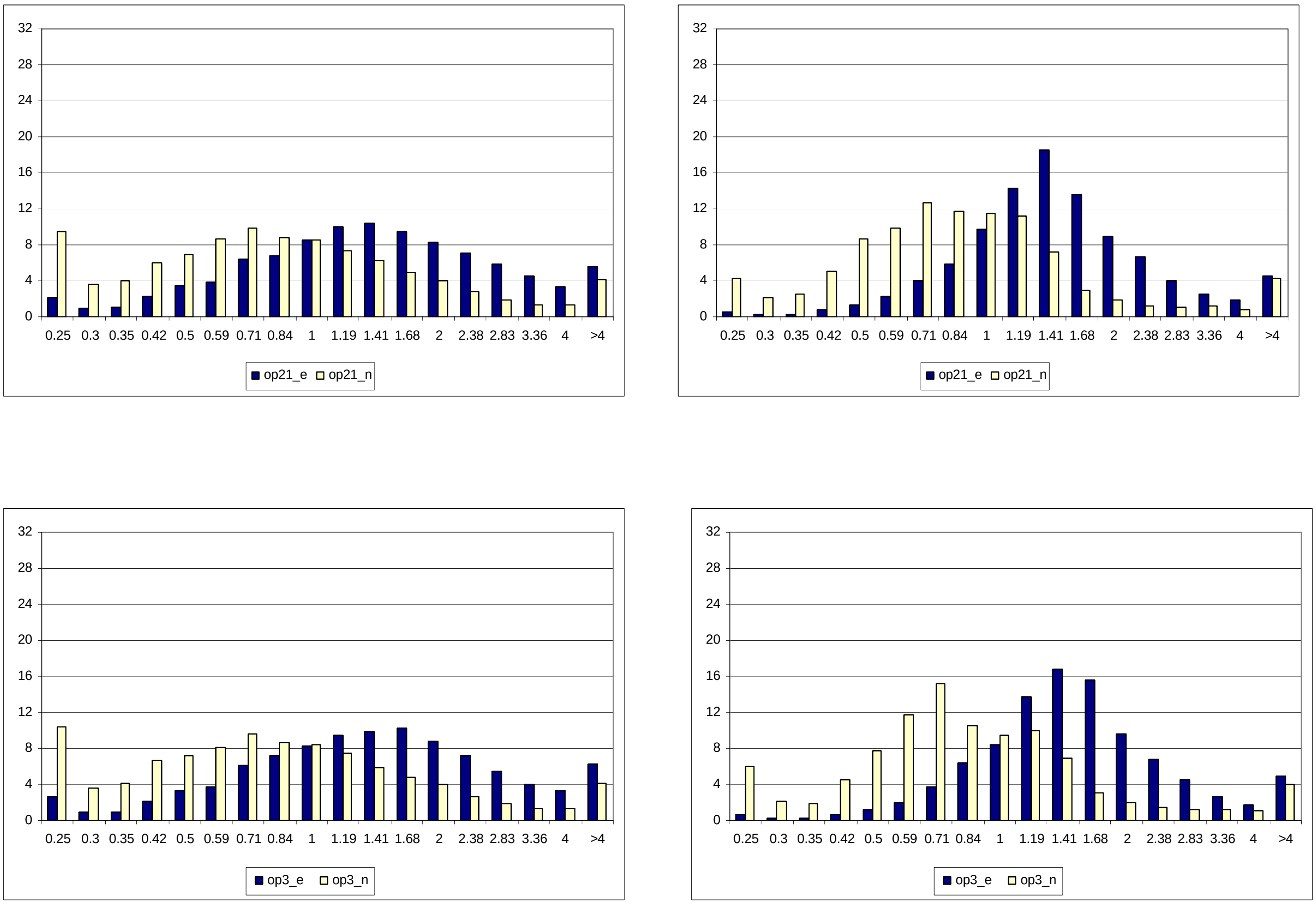
Productivity measure (deviation form 4-digit industry mean) calculated using OLS, GLS_fe, and Olley-Pakes 2-step coefficient estimates, splitting the sample into exporters and non-exporters, with and without the regression error



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

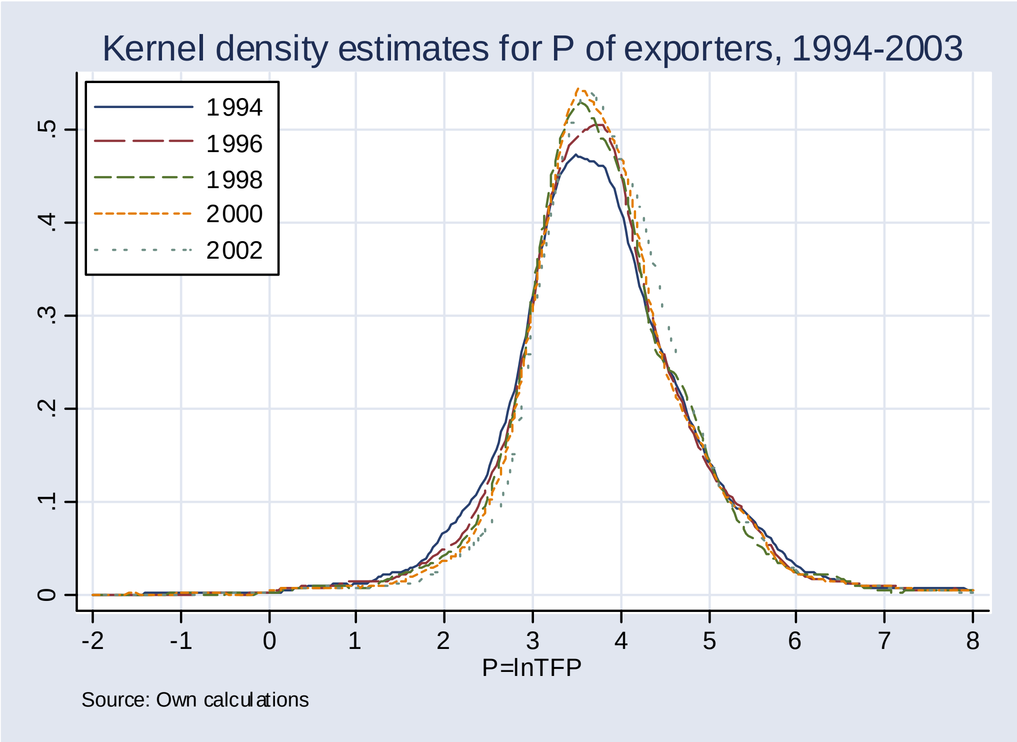
Figure 3(c): Comparing productivity of exporters and non-exporters

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



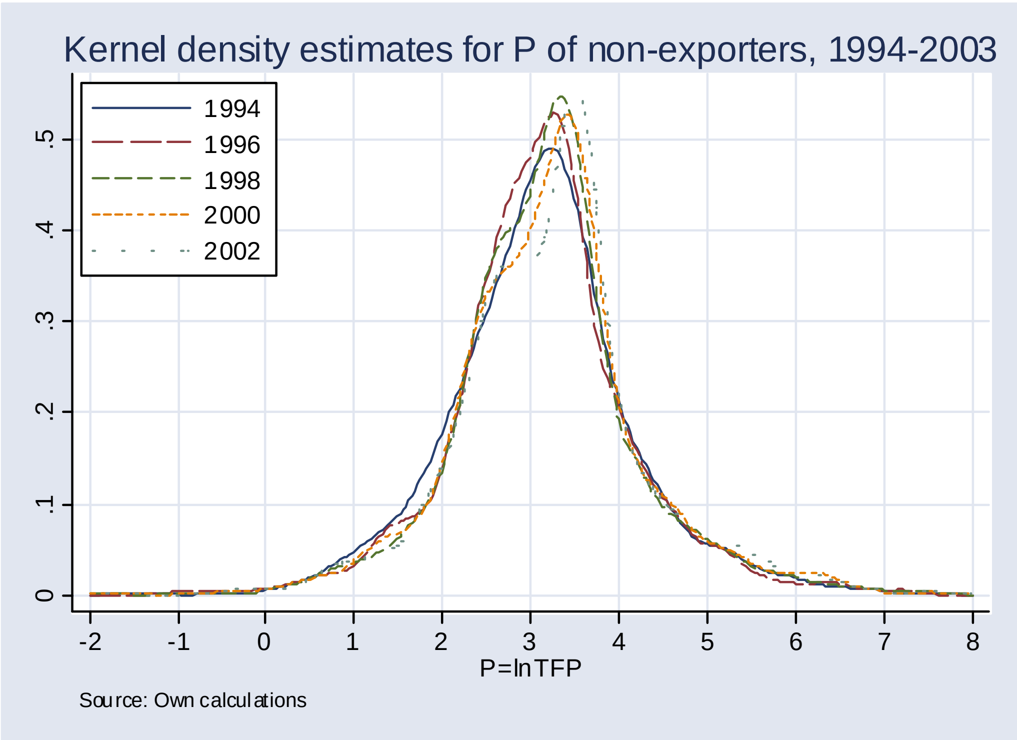
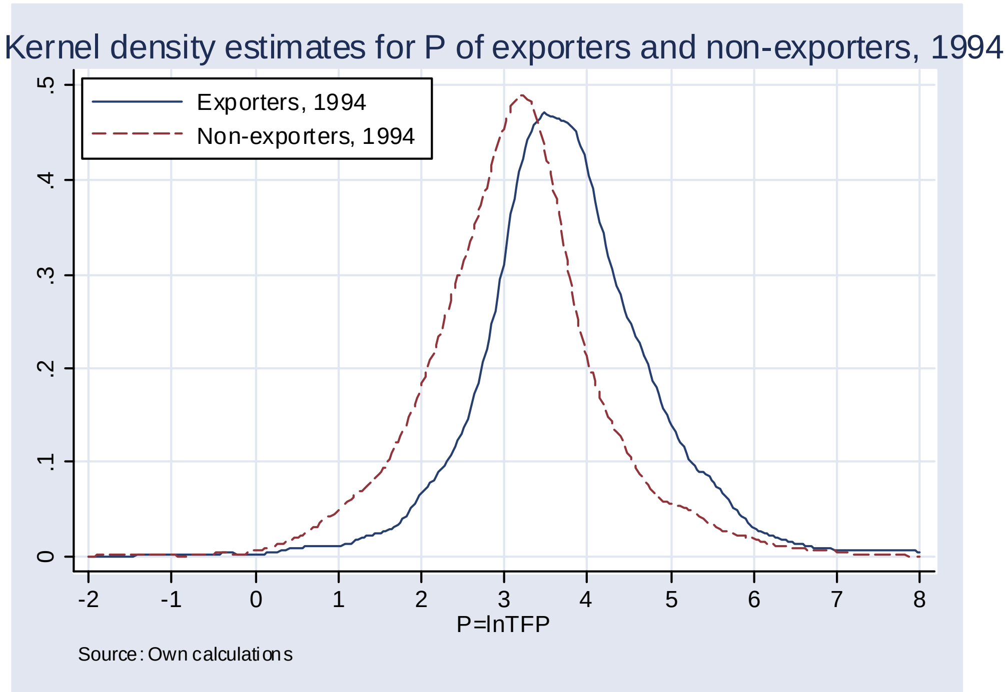


Figure 4(b): Distribution comparisons using Olley-Pakes 4-step estimates of productivity



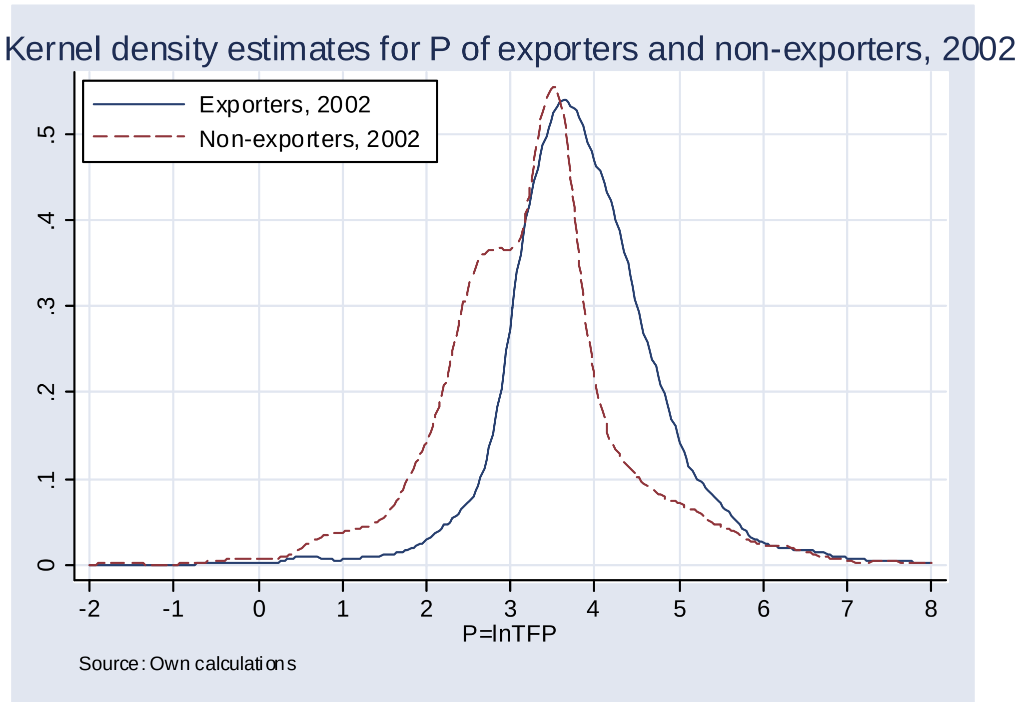
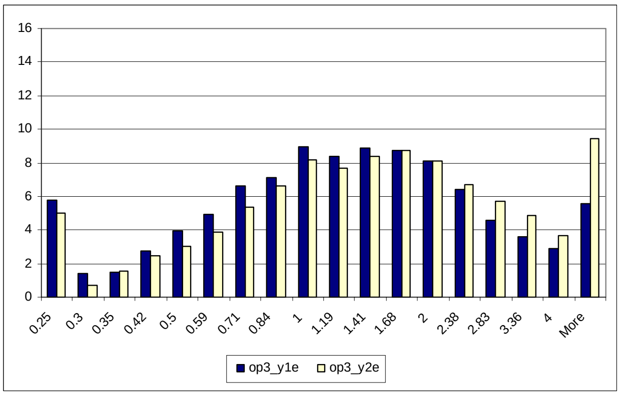


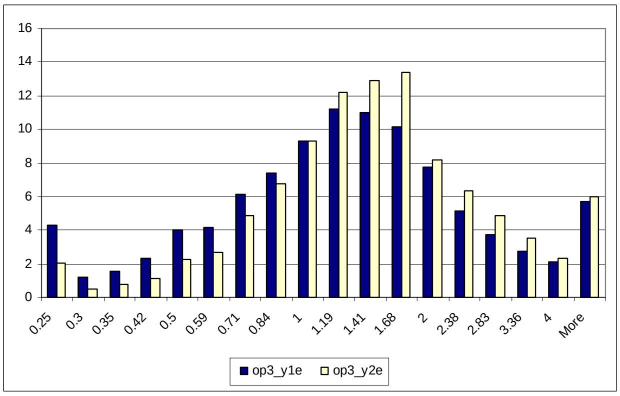
Figure 5: Comparing initial and last year productivity of exporters and non-exporters

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

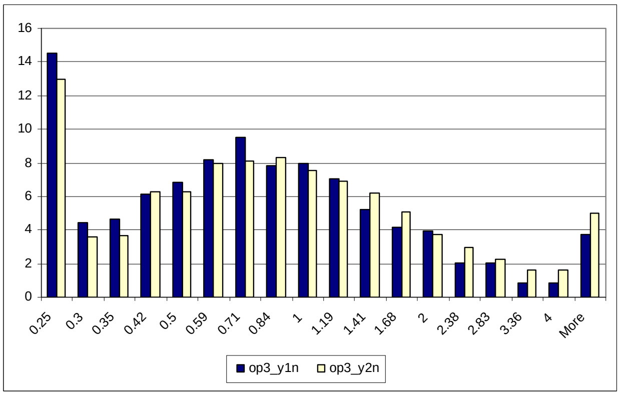
Exporters with Regression Error



Exporters without Regression Error



Non-Exporters with Regression Error



Non-Exporters without Regression Error

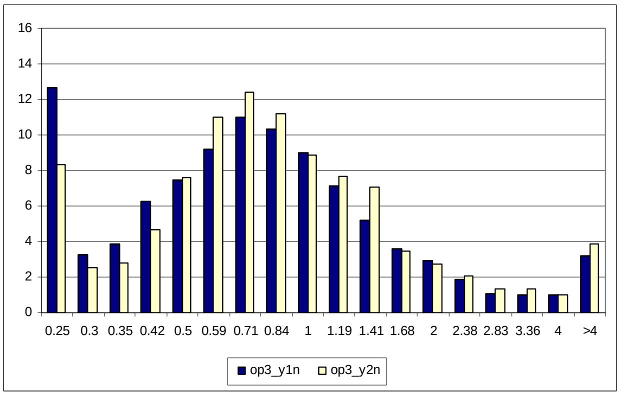
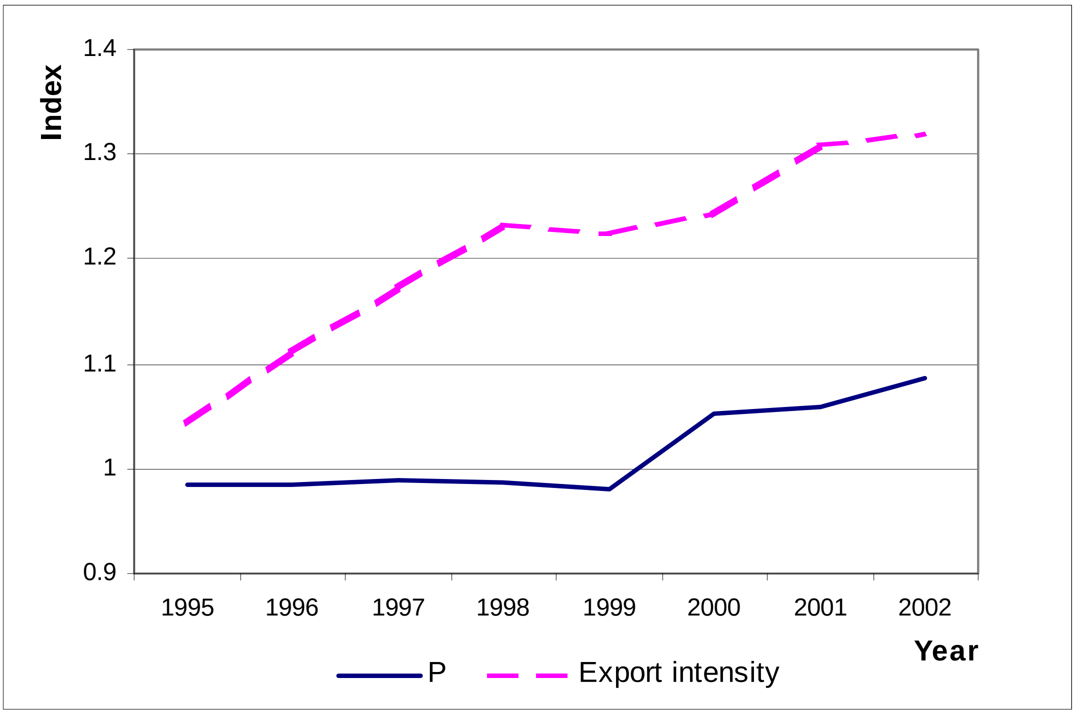


Figure 6: Aggregate productivity of the UK manufacturing and export intensity (exports/value added), 1994-2003



Note: Indexes are normalised at 1 for 1994.

Table 1: Company level facts on Exporting

Exporter share	**Percentage of all plants**	**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 productivity level

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	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 productivity level

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: Determinants of export status

Probit models of export status determinants (s.e. in parentheses)				
	Olley-Pakes 4-step estimates of productivity measure (without regression error)			
PRODUCTIVITY	**0.688** (0.031)	**0.703** (0.033)		**0.732** (0.032)
Age		**0.086** (0.026)		**0.087** (0.027)
Capital		**0.156** (0.015)		**0.158** (0.015)
First-stage error				**0.185** (0.030)
Time trend		Yes		Yes
	Olley-Pakes 4-step estimates of productivity measure (with regression error)			
PRODUCTIVITY	**0.494** (0.026)	**0.478** (0.026)		
Age		**0.115** (0.025)		
Capital		**0.156** (0.015)		
Time trend		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.

Table 6: Determinants of company Investment

Determinants of Company investment (s.e. in parentheses)			
	Olley-Pakes 4-step estimates of productivity measure (without regression error)		
PRODUCTIVITY	**0.482** (0.043)	**0.122** (0.021)	**0.158** (0.022)
Age		**-0.091** (0.020)	**-0.091** (0.020)
Capital		**0.847** (0.010)	**0.844** (0.010)
First-stage error			**0.121** (0.028)
Time trend		Yes	Yes
	Olley-Pakes 4-step estimates of productivity measure (with regression error)		
PRODUCTIVITY	**0.400** (0.038)	**0.135** (0.019)	
Age		**-0.090** (0.020)	
Capital		**0.847** (0.010)	
Time trend		Yes	
No observations	52,128	52,128	52,128

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.

Table 7: Percentiles of the cross-section distributions of company productivity

	Exporters					Non-exporters				
	1994	1996	1998	2000	2002	1994	1996	1998	2000	2002
Food and beverages (15), No of companies	138	160	172	176	176	127	164	189	205	218
25th percentile	3.787	3.726	4.024	3.989	4.020	1.339	1.418	1.654	1.569	1.738
Median	4.566	4.569	4.582	4.519	4.643	1.998	2.165	2.288	2.272	2.390
75th percentile	5.806	5.984	6.050	5.989	5.824	2.638	2.676	3.049	2.986	2.987
Wearing apparel (18), No of companies	57	66	75	81	81	44	66	63	57	50
25th percentile	3.853	3.848	3.873	3.904	4.187	2.626	2.530	2.413	2.346	2.835
Median	4.302	4.365	4.146	4.424	4.548	2.955	2.848	2.936	2.888	3.195
75th percentile	4.761	4.722	4.578	4.743	4.884	3.578	3.368	3.342	3.102	3.591
Pulp and paper (21), No of companies	97	121	126	130	127	66	82	88	93	85
25th percentile	2.383	2.384	2.449	2.517	2.615	1.845	1.812	1.662	1.726	1.885
Median	2.806	2.777	2.813	2.827	3.047	2.287	2.234	2.190	2.355	2.322
75th percentile	3.269	3.305	3.191	3.344	3.518	3.263	3.086	3.293	3.476	3.616
Publishing and printing (22), No of companies	350	429	468	505	494	503	752	777	803	747
25th percentile	3.160	3.152	3.132	3.204	3.239	3.113	3.125	3.211	3.241	3.332
Median	4.049	4.029	3.910	3.908	3.962	3.425	3.434	3.454	3.517	3.548
75th percentile	4.956	4.888	4.842	4.856	4.792	3.843	3.808	3.771	3.843	3.838
Chemicals and fuel (23 to 26), No of companies	599	695	747	836	822	196	274	294	319	340
25th percentile	3.306	3.326	3.380	3.395	3.486	2.213	2.267	2.406	2.336	2.427
Median	3.844	3.852	3.861	3.871	3.944	2.838	2.803	2.867	2.964	3.001
75th percentile	4.549	4.605	4.662	4.623	4.678	3.976	3.948	4.001	3.962	3.995
Basic and fabricated metals (27, 28), No of companies	550	678	726	758	726	326	516	520	510	484
25th percentile	3.176	3.242	3.224	3.253	3.204	2.338	2.469	2.467	2.424	2.403
Median	3.530	3.584	3.549	3.517	3.519	2.708	2.742	2.687	2.671	2.669

75^{th} percentile	3.928	3.943	3.860	3.822	3.859	3.033	3.104	3.005	2.989	2.963
Non-electrical machinery (29), No of companies	207	254	272	288	277	85	117	124	125	119
25^{th} percentile	3.716	3.742	3.846	3.674	3.823	3.106	2.914	3.032	3.102	3.136
Median	4.154	4.147	4.264	4.175	4.308	3.634	3.346	3.410	3.560	3.693
75^{th} percentile	4.535	4.600	4.669	4.626	4.648	4.021	3.910	3.869	4.061	4.106
Electrical machinery (30, 31, 32), No of companies	377	484	535	575	561	133	193	221	261	241
25^{th} percentile	2.459	2.677	2.985	3.187	3.378	2.281	2.279	2.396	2.486	2.715
Median	3.260	3.369	3.428	3.578	3.683	2.860	2.866	2.950	3.070	3.228
75^{th} percentile	3.721	3.775	3.785	3.930	3.996	3.432	3.356	3.473	3.605	3.657
Precision instruments (33), No of companies	159	196	212	233	222	43	61	62	66	63
25^{th} percentile	2.662	2.495	2.797	2.945	2.989	3.586	3.756	3.880	3.831	3.962
Median	3.122	3.211	3.175	3.189	3.222	4.074	4.119	4.230	4.336	4.456
75^{th} percentile	3.455	3.491	3.459	3.448	3.488	4.562	4.709	4.538	4.629	4.746
Transportation equipment (34, 35), No of companies	115	143	162	192	190	30	48	59	76	77
25^{th} percentile	3.095	3.160	3.145	3.104	3.203	3.334	2.760	2.708	3.026	3.076
Median	3.621	3.577	3.426	3.501	3.607	4.983	4.602	4.496	4.798	5.068
75^{th} percentile	3.997	4.086	3.872	3.886	3.939	6.017	5.751	5.343	5.751	5.692
Furniture and other (36), No of companies	330	406	445	490	484	131	219	236	262	262
25^{th} percentile	3.705	3.748	3.821	3.860	3.931	3.106	3.056	3.075	3.125	3.189
Median	3.974	3.982	4.072	4.072	4.147	3.372	3.330	3.383	3.397	3.495
75^{th} percentile	4.317	4.270	4.274	4.264	4.373	3.644	3.556	3.663	3.638	3.680
Total manufacturing, No of companies	2979	3632	3940	4264	4160	1684	2492	2633	2777	2686
25^{th} percentile	3.168	3.217	3.233	3.275	3.342	2.505	2.579	2.594	2.583	2.619
Median	3.708	3.732	3.713	3.736	3.807	3.126	3.121	3.177	3.222	3.296
75^{th} percentile	4.335	4.295	4.278	4.290	4.374	3.647	3.621	3.643	3.692	3.727

Table 8: Determinants of productivity growth

OLS models of productivity growth determinants (s.e. in parentheses)			
	Olley-Pakes 4-step estimates of productivity measure (without regression error)		
EXPORTER	0.018 (0.039)	0.023 (0.041)	-0.038 (0.042)
Initial productivity level	**-0.041** (0.018)	**-0.041** (0.018)	**0.042** (0.019)
Age		-0.015 (0.018)	-0.019 (0.017)
Capital		-0.002 (0.007)	-0.003 (0.007)
First-stage error			**-0.282** (0.028)
Time trend		Yes	Yes
	Olley-Pakes 4-step estimates of productivity measure (with regression error)		
EXPORTER	0.016 (0.022)	0.022 (0.024)	
Initial productivity level	**-0.036** (0.010)	**-0.037** (0.011)	
Age		-0.013 (0.010)	
Capital		-0.002 (0.004)	
Time trend		Yes	
No observations	50,955	50,955	50,955

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) is very low in the range 0 – 0.10.

Table 9: Olley-Pakes (1996) decomposition

Industry (SIC, 2-digit)	Year	Aggregate manufacturing productivity, P	Index of aggregate productivity, P	Index of unweighted mean productivity, $\overline{P}$	Index of $\sum_E \Delta s \Delta \omega$	Index of $\sum_{NE} \Delta s \Delta \omega$
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

Appendix I: Coefficient estimates within 4-digit SIC industries

SIC	Parameters	Estimation method												
		Export status not considered			Export status considered									
					Exogenous						Endogenous			
		OLS	GLSfe	OP2	OLS		GLS_fe		OP2		OP3		OP4	
					E	NE	E	NE	E	NE	E	NE	E	NE
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
1513	$\mathbf{b_l}$	**0.69**	**0.91**	**0.66**	**0.58**	**0.78**	**0.74**	**1.15**	**0.43**	**0.92**	**0.34**	**0.88**	**0.28**	**0.99**
	s.e	0.03	0.06	0.04	0.05	0.04	0.07	0.11	0.07	0.06	0.07	0.07	0.09	0.08
	$\mathbf{b_k}$	**0.24**	**0.09**	**0.27**	**0.30**	**0.16**	**0.13**	**0.04**	**0.25**	**0.12**	**0.30**	**0.19**	**0.33**	0.04
	s.e.	0.03	0.04	0.02	0.05	0.04	0.05	0.06	0.05	0.04	0.08	0.04	0.06	0.04
	$\mathbf{b_a}$	-0.01	**0.28**	**-0.29**	0.01	-0.04	**0.26**	**0.34**	0.01	**0.40**	0.20	**-0.15**	-0.03	0.12
	s.e.	0.03	0.09	0.07	0.04	0.03	0.11	0.13	0.08	0.12	0.16	0.07	0.09	0.12
	R^2	0.81	0.79	0.98	0.77	0.81	0.74	0.78	0.99	0.96	1.00	0.97	1.00	0.96
	No	848	848	561	366	482	366	482	243	318	243	318	221	305
1551	$\mathbf{b_l}$	**0.76**	**0.75**	**0.62**	**0.88**	**0.66**	**0.57**	**0.82**	**0.84**	**0.46**	**1.04**	**0.47**	**1.09**	**0.39**
	s.e	0.04	0.07	0.05	0.06	0.06	0.10	0.09	0.10	0.06	0.10	0.06	0.13	0.07
	$\mathbf{b_k}$	**0.20**	0.02	**0.35**	0.11	**0.24**	0.01	0.02	**0.15**	**0.42**	0.00	**0.51**	**0.12**	**0.49**
	s.e.	0.03	0.04	0.05	0.06	0.04	0.05	0.07	0.02	0.09	0.04	0.04	0.04	0.04
	$\mathbf{b_a}$	0.01	**0.19**	-0.03	0.02	0.02	0.15	0.21	0.05	**-0.40**	-0.05	-0.08	-0.00	-0.13
	s.e.	0.03	0.08	0.10	0.04	0.04	0.13	0.11	0.04	0.15	0.16	0.06	0.00	0.07
	R^2	0.84	0.82	0.99	0.92	0.77	0.91	0.73	0.96	0.99	0.99	0.99	0.99	1.00
	No	537	537	368	182	355	182	355	125	243	125	243	121	230
1584	$\mathbf{b_l}$	**0.75**	**0.29**	**0.51**	**0.70**	**0.73**	0.11	**0.73**	**0.33**	**0.56**	**0.36**	**0.61**	**0.31**	0.44
	s.e	0.06	0.06	0.07	0.07	0.11	0.06	0.16	0.07	0.20	0.06	0.23	0.08	1.08
	$\mathbf{b_k}$	**0.23**	**0.16**	0.16	**0.12**	**0.40**	**0.20**	0.05	0.01	**0.58**	0.03	**0.40**	0.05	**0.42**
	s.e.	0.04	0.04	0.10	0.05	0.08	0.04	0.15	0.08	0.04	0.04	0.04	0.04	0.07
	$\mathbf{b_a}$	**0.29**	**-0.24**	-0.18	**0.41**	0.09	0.08	**-0.71**	-0.31	**-0.32**	0.00	0.35	**1.05**	0.05
	s.e.	0.04	0.09	0.31	0.05	0.06	0.10	0.16	0.26	0.11	0.00	0.22	0.11	0.16
	R^2	0.81	0.64	0.98	0.72	0.93	0.65	0.61	0.99	1.00	1.00	1.00	1.00	0.96
	No	431	431	283	291	140	291	140	203	80	203	80	194	68
1589	$\mathbf{b_l}$	**0.75**	**0.42**	**0.75**	**0.81**	**0.72**	**0.71**	**0.26**	**0.77**	**0.70**	**0.73**	**0.65**	**0.79**	**0.63**
	s.e	0.03	0.04	0.04	0.04	0.04	0.08	0.05	0.05	0.05	0.05	0.05	0.06	0.06
	$\mathbf{b_k}$	**0.20**	**0.15**	**0.06**	**0.12**	**0.27**	0.03	**0.21**	0.06	**0.26**	**0.09**	**0.16**	**0.04**	**0.19**
	s.e.	0.02	0.03	0.03	0.04	0.04	0.04	0.05	0.04	0.04	0.02	0.06	0.02	0.03
	$\mathbf{b_a}$	**0.13**	**0.21**	**0.28**	**0.10**	**0.14**	0.09	0.18	**0.66**	0.14	0.07	0.11	**0.46**	**0.48**
	s.e.	0.02	0.08	0.04	0.03	0.04	0.11	0.10	0.13	0.08	0.11	0.14	0.06	0.07
	R^2	0.85	0.84	0.98	0.84	0.86	0.84	0.84	0.98	0.99	0.99	0.99	0.99	0.99
	No	1041	1041	735	571	470	571	470	416	319	416	319	392	295
1591	$\mathbf{b_l}$	**0.82**	**0.72**	**0.83**	**0.95**	**0.60**	**0.83**	0.19	**0.92**	**0.89**	**1.00**	**0.70**	**0.76**	**0.73**
	s.e	0.07	0.08	0.09	0.08	0.10	0.09	0.18	0.11	0.21	0.13	0.28	0.16	0.27
	$\mathbf{b_k}$	**0.22**	0.04	**0.17**	**0.17**	**0.41**	0.01	0.14	0.02	**0.71**	**0.12**	0.12	**0.24**	0.12
	s.e.	0.06	0.07	0.02	0.07	0.08	0.08	0.18	0.08	0.26	0.05	0.14	0.06	0.10
	$\mathbf{b_a}$	**0.26**	0.12	**0.52**	-0.03	**0.42**	-0.23	0.48	**0.55**	**-1.27**	-0.00	**0.55**	0.10	**0.51**
	s.e.	0.05	0.18	0.06	0.07	0.06	0.25	0.25	0.19	0.46	0.00	0.12	0.09	0.10
	R^2	0.76	0.75	0.98	0.77	0.85	0.74	0.74	0.98	0.92	0.99	0.97	0.97	0.97
	No	286	286	188	152	134	152	134	103	85	103	85	93	79
1596	$\mathbf{b_l}$	**0.54**	**0.39**	**0.42**	0.00	**0.67**	**0.64**	**0.37**	**0.26**	**0.42**	0.07	**0.50**	0.11	**0.47**
	s.e	0.05	0.05	0.06	0.12	0.05	0.10	0.06	0.08	0.07	0.14	0.07	0.19	0.07
	$\mathbf{b_k}$	**0.40**	**0.07**	**0.34**	**0.96**	**0.30**	0.03	**0.08**	**0.59**	**0.24**	**0.89**	0.09	**0.59**	**0.44**
	s.e.	0.04	0.03	0.04	0.13	0.04	0.07	0.04	0.07	0.04	0.04	0.06	0.14	0.02
	$\mathbf{b_a}$	**-0.23**	0.00	-0.02	**-0.38**	**-0.25**	-0.04	0.01	**-0.40**	-0.17	**-0.70**	-0.01	-0.80	**-0.29**
	s.e.	0.04	0.07	0.10	0.10	0.04	0.11	0.09	0.14	0.12	0.09	0.01	0.86	0.06

	R^2	0.87	0.84	0.99	0.85	0.90	0.77	0.88	1.00	0.99	1.00	1.00	0.95	0.99
	No	301	301	212	91	210	91	210	69	143	69	143	61	130
1598	$\mathbf{b_l}$	**0.72**	**0.78**	**0.58**	**0.57**	**0.88**	**0.53**	**1.06**	0.22	**0.79**	0.30	**0.88**	0.21	**0.98**
	s.e	0.07	0.10	0.10	0.15	0.06	0.16	0.14	0.22	0.11	0.23	0.13	0.40	0.14
	$\mathbf{b_k}$	**0.31**	**0.27**	**0.59**	**0.26**	**0.30**	**0.49**	0.05	**0.37**	**0.40**	**0.35**	**0.23**	**0.18**	**0.31**
	s.e.	0.05	0.07	0.03	0.11	0.04	0.11	0.10	0.07	0.04	0.08	0.02	0.06	0.02
	$\mathbf{b_a}$	-0.00	**0.50**	**0.24**	**-0.27**	**0.09**	1.30	0.40	-0.06	-0.12	**-1.52**	0.10	-0.09	0.01
	s.e.	0.04	0.23	0.04	0.10	0.04	0.68	0.24	0.13	0.08	0.34	0.06	0.18	0.01
	R^2	0.78	0.72	0.98	0.59	0.91	0.34	0.86	0.99	0.99	0.99	0.99	1.00	0.99
	No	398	398	275	167	231	167	231	115	160	115	160	98	156
1822	$\mathbf{b_l}$	**0.48**	**0.45**	**0.38**	**0.54**	**0.38**	**0.53**	**0.32**	**0.41**	**0.31**	**0.39**	**0.29**	**0.43**	**0.36**
	s.e	0.03	0.04	0.03	0.03	0.04	0.05	0.05	0.04	0.05	0.04	0.05	0.04	0.06
	$\mathbf{b_k}$	**0.36**	**0.17**	**0.23**	**0.23**	**0.45**	**0.12**	**0.25**	**0.23**	**0.34**	**0.12**	**0.32**	**0.22**	**0.46**
	s.e.	0.02	0.02	0.04	0.02	0.03	0.03	0.04	0.03	0.03	0.05	0.04	0.06	0.05
	$\mathbf{b_a}$	-0.02	**0.28**	**0.41**	**-0.07**	0.04	0.05	**0.58**	**0.38**	-0.08	**0.84**	0.00	-0.00	**-0.20**
	s.e.	0.03	0.08	0.12	0.03	0.04	0.10	0.12	0.11	0.15	0.18	0.00	0.15	0.10
	R^2	0.75	0.71	0.98	0.73	0.73	0.72	0.62	0.99	0.98	0.99	0.98	0.99	0.98
	No	1404	1404	930	762	642	762	642	533	397	533	397	515	379
2112	$\mathbf{b_l}$	**0.84**	**0.53**	**0.83**	**0.67**	**1.14**	**0.79**	0.18	**0.69**	**1.06**	**0.70**	**1.06**	**0.90**	**0.99**
	s.e	0.04	0.10	0.06	0.05	0.09	0.11	0.19	0.08	0.11	0.08	0.14	0.10	0.19
	$\mathbf{b_k}$	**0.07**	**0.24**	0.04	**0.22**	**-0.12**	**0.12**	**0.32**	**0.20**	0.11	**0.22**	**0.21**	**0.14**	**0.22**
	s.e.	0.03	0.05	0.04	0.03	0.05	0.05	0.09	0.01	0.13	0.04	0.03	0.03	0.05
	$\mathbf{b_a}$	-0.01	-0.13	0.06	**-0.09**	**0.24**	0.11	**-0.58**	**-0.10**	0.32	-0.00	0.00	-0.00	**0.75**
	s.e.	0.03	0.11	0.09	0.03	0.06	0.12	0.21	0.04	0.30	0.11	0.00	0.02	0.12
	R^2	0.80	0.77	0.98	0.83	0.76	0.80	0.45	0.99	0.97	0.99	0.98	0.99	0.98
	No	624	624	407	386	238	386	238	269	138	269	138	264	121
2121	$\mathbf{b_l}$	**0.66**	**0.80**	**0.59**	**0.51**	**0.86**	**0.71**	**1.01**	**0.48**	**0.76**	**0.52**	**0.77**	**0.61**	**0.72**
	s.e	0.03	0.04	0.03	0.04	0.04	0.04	0.06	0.05	0.04	0.06	0.05	0.06	0.05
	$\mathbf{b_k}$	**0.25**	**0.12**	**0.33**	**0.36**	**0.14**	0.05	**0.22**	**0.32**	**0.28**	**0.23**	**0.31**	**0.26**	**0.34**
	s.e.	0.02	0.03	0.01	0.03	0.02	0.03	0.04	0.03	0.02	0.02	0.02	0.02	0.02
	$\mathbf{b_a}$	**-0.08**	**0.25**	**-0.09**	**-0.08**	**-0.09**	**0.27**	**0.33**	-0.09	**-0.19**	-0.00	-0.03	-0.09	**-0.29**
	s.e.	0.02	0.08	0.03	0.03	0.03	0.10	0.12	0.09	0.06	0.00	0.04	0.05	0.06
	R^2	0.81	0.76	0.99	0.76	0.84	0.63	0.80	0.99	0.99	0.99	0.99	0.99	0.99
	No	1256	1256	826	625	631	625	631	427	399	427	399	379	364
2125	$\mathbf{b_l}$	**0.87**	**0.59**	**0.78**	**0.67**	**1.08**	**0.32**	**0.90**	**0.61**	**1.07**	**0.67**	**1.06**	**0.56**	**0.97**
	s.e	0.04	0.08	0.05	0.05	0.08	0.09	0.14	0.06	0.09	0.06	0.12	0.08	0.16
	$\mathbf{b_k}$	**0.15**	**0.09**	**0.20**	**0.20**	0.05	**0.12**	0.02	**0.23**	0.01	**0.22**	0.02	**0.22**	0.01
	s.e.	0.02	0.04	0.02	0.03	0.05	0.04	0.06	0.03	0.02	0.03	0.04	0.02	0.05
	$\mathbf{b_a}$	**-0.09**	**0.31**	-0.03	**-0.07**	-0.05	**0.30**	0.26	-0.03	**-0.20**	**-0.17**	-0.00	**-0.15**	0.15
	s.e.	0.02	0.06	0.04	0.03	0.05	0.07	0.14	0.04	0.09	0.07	0.07	0.02	0.08
	R^2	0.83	0.72	0.98	0.78	0.84	0.59	0.80	0.99	0.97	0.99	0.98	1.00	0.99
	No	531	531	368	330	201	330	201	240	128	240	128	186	84
2211	$\mathbf{b_l}$	**0.99**	**0.54**	**0.95**	**0.96**	**0.98**	**0.50**	**0.63**	**0.85**	**1.01**	**0.83**	**0.97**	**0.84**	**0.92**
	s.e	0.02	0.04	0.03	0.03	0.05	0.04	0.08	0.03	0.06	0.04	0.06	0.04	0.07
	$\mathbf{b_k}$	**0.08**	**0.05**	0.01	**0.04**	**0.12**	**0.08**	0.02	0.01	0.05	0.00	0.00	**0.05**	0.04
	s.e.	0.02	0.02	0.03	0.02	0.03	0.02	0.03	0.02	0.05	0.02	0.04	0.02	0.06
	$\mathbf{b_a}$	-0.01	**0.20**	**0.48**	-0.01	-0.04	**0.26**	0.11	0.13	**-0.97**	-0.11	**-0.22**	-0.00	-0.01
	s.e.	0.02	0.07	0.20	0.03	0.04	0.09	0.11	0.07	0.44	0.07	0.10	0.00	0.19
	R^2	0.80	0.78	0.96	0.80	0.72	0.76	0.69	0.98	0.95	0.98	0.96	0.98	0.96
	No	2014	2014	1294	1328	686	1328	686	892	402	892	402	843	376
2212	$\mathbf{b_l}$	**0.44**	**0.54**	**0.38**	**0.78**	**0.38**	**1.01**	**0.47**	**0.80**	**0.29**	**0.75**	**0.34**	**0.99**	**0.22**
	s.e	0.03	0.04	0.03	0.07	0.03	0.09	0.05	0.06	0.04	0.08	0.04	0.11	0.04
	$\mathbf{b_k}$	**0.44**	**0.24**	**0.15**	**0.15**	**0.47**	0.03	**0.25**	**0.10**	**0.47**	0.09	**0.38**	0.02	**0.26**
	s.e.	0.02	0.02	0.06	0.05	0.02	0.04	0.03	0.03	0.06	0.05	0.04	0.02	0.05
	$\mathbf{b_a}$	**-0.06**	**0.45**	-0.63	-0.04	**-0.06**	**-0.77**	**0.58**	**0.24**	-0.06	0.12	**0.52**	0.00	**-0.29**
	s.e.	0.02	0.07	0.39	0.08	0.02	0.15	0.08	0.10	0.54	0.12	0.15	0.06	0.10

	R^2	0.85	0.78	0.99	0.85	0.84	0.78	0.68	0.99	0.99	0.99	1.00	0.99	0.99
	No	1051	1051	709	208	843	208	843	153	556	153	556	147	509
2213	$\mathbf{b_l}$	**0.90**	**0.71**	**0.86**	**0.80**	**0.93**	**0.64**	**0.77**	**0.65**	**0.93**	**0.69**	**0.92**	**0.66**	**0.92**
	s.e	0.02	0.03	0.03	0.04	0.03	0.04	0.05	0.05	0.03	0.05	0.03	0.05	0.03
	$\mathbf{b_k}$	**0.14**	**0.04**	**0.06**	**0.14**	**0.14**	**0.10**	0.00	**0.13**	0.03	**0.16**	**0.06**	**0.14**	**0.08**
	s.e.	0.02	0.02	0.03	0.03	0.02	0.02	0.02	0.06	0.04	0.03	0.03	0.02	0.02
	$\mathbf{b_a}$	**0.05**	**0.30**	**0.24**	**0.10**	-0.00	0.11	**0.51**	0.04	0.13	**-0.19**	0.00	**0.18**	0.00
	s.e.	0.02	0.06	0.07	0.04	0.03	0.07	0.09	0.23	0.21	0.08	0.00	0.07	0.00
	R^2	0.74	0.71	0.95	0.70	0.73	0.70	0.64	0.96	0.96	0.97	0.96	0.98	0.96
	No	2378	2378	1515	936	1442	936	1442	634	881	634	881	621	850
2215	$\mathbf{b_l}$	**0.77**	**0.87**	**0.80**	**0.69**	**0.80**	**0.98**	**0.69**	**0.70**	**0.96**	**0.78**	**0.94**	**0.65**	**0.90**
	s.e	0.04	0.04	0.04	0.05	0.05	0.05	0.07	0.06	0.08	0.07	0.08	0.08	0.09
	$\mathbf{b_k}$	**0.19**	0.04	0.01	**0.19**	**0.22**	0.01	0.06	**0.24**	0.02	0.07	**0.14**	**0.28**	0.02
	s.e.	0.02	0.03	0.05	0.03	0.04	0.05	0.04	0.03	0.06	0.04	0.05	0.04	0.03
	$\mathbf{b_a}$	**0.18**	**0.52**	0.22	**0.23**	0.08	**0.64**	**0.39**	**0.24**	0.16	**0.35**	0.01	**0.36**	-0.00
	s.e.	0.03	0.08	0.15	0.04	0.05	0.10	0.12	0.07	0.22	0.07	0.07	0.10	0.00
	R^2	0.77	0.74	0.97	0.76	0.75	0.72	0.71	0.98	0.95	0.99	0.97	0.99	0.99
	No	886	886	536	480	406	480	406	311	225	311	225	275	209
2222	$\mathbf{b_l}$	**0.74**	**0.62**	**0.75**	**0.78**	**0.73**	**0.76**	**0.57**	**0.76**	**0.74**	**0.72**	**0.71**	**0.72**	**0.70**
	s.e	0.01	0.02	0.01	0.02	0.01	0.04	0.02	0.02	0.02	0.03	0.02	0.03	0.02
	$\mathbf{b_k}$	**0.18**	**0.14**	**0.10**	**0.07**	**0.20**	**0.06**	**0.17**	**0.14**	**0.10**	**0.15**	**0.14**	**0.17**	**0.14**
	s.e.	0.01	0.01	0.01	0.02	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.03	0.02
	$\mathbf{b_a}$	**-0.06**	**0.29**	**-0.21**	**-0.04**	**-0.07**	**0.34**	**0.26**	**-0.24**	**-0.36**	-0.00	**-0.20**	**-0.12**	-0.00
	s.e.	0.01	0.03	0.02	0.02	0.01	0.05	0.03	0.06	0.10	0.00	0.06	0.05	0.01
	R^2	0.80	0.75	0.98	0.72	0.78	0.63	0.73	0.98	0.98	0.98	0.98	0.98	0.98
	No	6791	6791	4382	1913	4878	1913	4878	1357	3025	1357	3025	1277	2870
2320	$\mathbf{b_l}$	**0.55**	**0.14**	**0.51**	**0.59**	**0.52**	**0.33**	0.02	**0.58**	0.34	**0.63**	0.01	**0.62**	0.42
	s.e	0.04	0.05	0.05	0.04	0.10	0.06	0.16	0.05	0.19	0.05	0.26	0.06	0.28
	$\mathbf{b_k}$	**0.41**	**0.31**	**0.38**	**0.36**	**0.45**	**0.16**	**0.39**	**0.36**	**0.38**	0.08	**0.56**	**0.24**	**0.36**
	s.e.	0.03	0.03	0.01	0.03	0.05	0.04	0.07	0.02	0.03	0.05	0.05	0.02	0.03
	$\mathbf{b_a}$	0.02	-0.20	-0.03	-0.09	**0.22**	-0.22	-0.42	**-0.13**	0.04	-0.00	0.47	**-0.40**	**0.44**
	s.e.	0.05	0.20	0.07	0.05	0.11	0.18	0.55	0.04	0.11	0.01	0.24	0.04	0.10
	R^2	0.90	0.86	0.99	0.93	0.84	0.91	0.68	0.97	0.99	0.99	0.99	1.00	0.99
	No	412	412	298	285	127	285	127	207	91	207	91	197	75
2413	$\mathbf{b_l}$	**0.72**	**0.65**	**0.68**	**0.70**	**0.79**	**0.61**	**1.06**	**0.65**	**0.87**	**0.63**	**0.97**	**0.61**	**0.96**
	s.e	0.03	0.06	0.04	0.04	0.06	0.07	0.16	0.04	0.07	0.04	0.08	0.05	0.10
	$\mathbf{b_k}$	**0.18**	**0.09**	**0.22**	**0.17**	**0.18**	**0.11**	0.05	**0.22**	**0.14**	**0.14**	**0.13**	**0.15**	0.04
	s.e.	0.02	0.04	0.02	0.02	0.04	0.04	0.07	0.03	0.04	0.02	0.02	0.03	0.03
	$\mathbf{b_a}$	0.02	-0.06	-0.07	0.04	0.01	0.05	**-0.69**	-0.00	**0.59**	**0.19**	0.10	**0.38**	0.11
	s.e.	0.03	0.11	0.05	0.03	0.06	0.13	0.20	0.09	0.17	0.07	0.08	0.09	0.07
	R^2	0.78	0.77	0.97	0.74	0.83	0.74	0.75	0.97	0.98	0.98	0.99	0.98	0.98
	No	1168	1168	799	881	287	881	287	617	182	617	182	564	171
2416	$\mathbf{b_l}$	**0.59**	**0.54**	**0.54**	**0.59**	**0.61**	**0.54**	**0.58**	**0.51**	**0.78**	**0.50**	**0.86**	**0.45**	**0.90**
	s.e	0.03	0.04	0.04	0.03	0.09	0.05	0.10	0.04	0.11	0.04	0.11	0.04	0.13
	$\mathbf{b_k}$	**0.25**	**0.11**	0.01	**0.22**	**0.26**	**0.09**	**0.14**	**0.26**	**0.41**	0.04	**0.26**	**0.16**	**0.11**
	s.e.	0.02	0.04	0.07	0.02	0.05	0.04	0.07	0.03	0.06	0.06	0.06	0.04	0.04
	$\mathbf{b_a}$	**0.09**	**0.38**	**2.30**	**0.07**	0.10	**0.27**	**0.55**	**-0.22**	**-0.68**	**0.33**	-0.00	-0.13	**0.13**
	s.e.	0.03	0.08	0.59	0.03	0.08	0.10	0.17	0.07	0.18	0.12	0.01	0.11	0.12
	R^2	0.69	0.63	0.98	0.66	0.67	0.61	0.60	0.99	0.97	0.99	0.97	0.99	0.99
	No	1178	1178	819	914	264	914	264	654	165	654	165	611	136
2430	$\mathbf{b_l}$	**0.82**	**0.87**	**0.82**	**0.87**	**0.95**	**0.88**	**0.82**	**0.86**	**0.76**	**0.82**	**0.53**	**0.89**	**0.46**
	s.e	0.04	0.06	0.05	0.05	0.09	0.06	0.13	0.06	0.13	0.06	0.18	0.07	0.10
	$\mathbf{b_k}$	**0.12**	**0.11**	**0.08**	0.04	**0.15**	**0.10**	**0.17**	0.02	**0.34**	0.07	**0.16**	**0.10**	**0.55**
	s.e.	0.03	0.04	0.03	0.04	0.06	0.05	0.08	0.04	0.06	0.04	0.07	0.02	0.06
	$\mathbf{b_a}$	0.04	**0.20**	**0.17**	0.02	0.08	**0.21**	0.04	-0.15	0.28	0.00	**-0.93**	0.00	0.00
	s.e.	0.03	0.09	0.07	0.03	0.06	0.10	0.20	0.09	0.15	0.04	0.20	0.03	0.00

	R^2	0.84	0.83	0.98	0.83	0.88	0.82	0.88	0.98	0.99	0.99	1.00	0.99	1.00
	No	554	554	374	449	105	449	105	315	59	315	59	296	55
2441	$\mathbf{b_l}$	**1.10**	**0.93**	**0.96**	**1.14**	**0.83**	**0.91**	**1.03**	**1.03**	**0.47**	**1.03**	**0.49**	**1.06**	**0.91**
	s.e	0.04	0.07	0.05	0.04	0.12	0.08	0.11	0.05	0.14	0.05	0.12	0.06	0.21
	$\mathbf{b_k}$	0.04	0.04	0.01	**0.08**	**0.16**	0.02	0.10	**0.08**	**0.22**	0.03	**0.34**	**0.21**	**0.20**
	s.e.	0.03	0.04	0.04	0.03	0.08	0.04	0.07	0.04	0.08	0.03	0.09	0.03	0.02
	$\mathbf{b_a}$	**0.08**	**0.29**	0.14	**0.09**	0.02	**0.31**	0.24	**0.62**	**0.66**	0.08	**-0.36**	**0.22**	-0.05
	s.e.	0.03	0.10	0.14	0.03	0.07	0.12	0.14	0.21	0.13	0.06	0.15	0.07	0.04
	R^2	0.79	0.78	0.96	0.82	0.67	0.81	0.63	0.96	0.98	0.96	0.99	0.96	0.99
	No	1050	1050	727	788	262	788	262	554	173	554	173	529	157
2442	$\mathbf{b_l}$	**1.05**	**0.39**	**0.98**	**1.02**	**0.98**	**0.49**	0.14	**1.02**	0.04	**0.98**	0.21	**0.92**	0.25
	s.e	0.07	0.07	0.10	0.08	0.17	0.08	0.15	0.11	0.30	0.11	0.50	0.11	0.38
	$\mathbf{b_k}$	0.05	**0.21**	**0.17**	0.05	0.04	**0.14**	**0.54**	**0.07**	**0.56**	**0.19**	**0.52**	**0.09**	**0.08**
	s.e.	0.04	0.05	0.06	0.05	0.12	0.05	0.13	0.02	0.02	0.03	0.04	0.04	0.04
	$\mathbf{b_a}$	0.05	**0.27**	-0.25	0.08	0.02	**0.28**	0.18	-0.20	**0.75**	0.00	**0.67**	**-0.31**	**0.30**
	s.e.	0.05	0.12	0.15	0.06	0.15	0.14	0.24	0.12	0.10	0.00	0.18	0.11	0.15
	R^2	0.73	0.66	0.95	0.69	0.79	0.63	0.66	0.94	1.00	0.96	1.00	0.97	0.98
	No	381	381	264	291	90	291	90	201	63	201	63	185	58
2451	$\mathbf{b_l}$	**0.55**	**0.37**	**0.29**	**0.39**	**0.96**	**0.39**	0.20	**0.24**	0.68	**0.45**	0.20	**0.43**	**0.86**
	s.e	0.07	0.07	0.08	0.09	0.09	0.09	0.16	0.10	0.53	0.10	0.77	0.12	0.19
	$\mathbf{b_k}$	**0.36**	0.09	0.05	**0.42**	**0.14**	0.09	0.06	**0.31**	**0.21**	**0.35**	**0.31**	**0.35**	0.16
	s.e.	0.05	0.05	0.10	0.07	0.06	0.06	0.11	0.04	0.03	0.05	0.04	0.02	0.20
	$\mathbf{b_a}$	**0.20**	0.02	0.12	**0.17**	**0.32**	0.04	-0.08	0.05	**0.19**	**0.20**	0.09	0.15	0.30
	s.e.	0.04	0.10	0.22	0.05	0.05	0.12	0.13	0.07	0.06	0.08	0.15	0.13	0.28
	R^2	0.85	0.84	0.99	0.80	0.97	0.78	0.85	0.99	1.00	1.00	1.00	0.97	0.97
	No	290	290	202	205	85	205	85	145	57	145	57	136	53
2452	$\mathbf{b_l}$	**0.58**	**0.44**	**0.45**	**0.46**	**0.68**	**0.34**	**0.54**	**0.30**	**0.62**	**0.28**	**0.67**	**0.26**	**0.44**
	s.e	0.06	0.06	0.06	0.08	0.10	0.08	0.11	0.09	0.11	0.09	0.17	0.09	0.22
	$\mathbf{b_k}$	**0.26**	**0.12**	**0.31**	**0.31**	**0.20**	**0.13**	0.12	**0.30**	**0.26**	**0.24**	**0.35**	**0.18**	**0.26**
	s.e.	0.04	0.03	0.02	0.05	0.06	0.03	0.07	0.02	0.07	0.05	0.07	0.04	0.07
	$\mathbf{b_a}$	0.08	0.02	-0.12	0.04	**0.22**	0.05	-0.20	**0.12**	-0.04	0.01	**-0.86**	**-0.18**	**0.90**
	s.e.	0.05	0.09	0.07	0.05	0.10	0.09	0.27	0.06	0.26	0.07	0.28	0.08	0.20
	R^2	0.71	0.71	0.98	0.71	0.70	0.71	0.66	0.99	0.99	0.99	0.99	1.00	1.00
	No	582	582	407	380	202	380	202	265	142	265	142	235	130
2466	$\mathbf{b_l}$	**0.78**	**0.83**	**0.72**	**0.86**	**0.56**	**0.88**	**0.63**	**0.78**	**0.33**	**0.79**	**0.22**	**0.81**	**0.28**
	s.e	0.03	0.03	0.03	0.03	0.09	0.03	0.10	0.03	0.11	0.03	0.11	0.04	0.14
	$\mathbf{b_k}$	**0.12**	**0.10**	**0.16**	0.03	**0.29**	**0.06**	**0.11**	**0.09**	**0.60**	**0.09**	**0.34**	**0.14**	**0.43**
	s.e.	0.02	0.02	0.03	0.02	0.05	0.02	0.05	0.02	0.05	0.03	0.02	0.04	0.04
	$\mathbf{b_a}$	0.03	**0.37**	**0.37**	**0.04**	**-0.14**	**0.18**	**0.92**	-0.08	0.02	0.07	-0.00	0.00	**-0.43**
	s.e.	0.02	0.06	0.18	0.02	0.07	0.06	0.16	0.07	0.14	0.08	0.00	0.00	0.14
	R^2	0.77	0.68	0.98	0.80	0.70	0.79	0.68	0.98	0.98	0.98	0.99	0.98	0.99
	No	1658	1658	1124	1317	341	1317	341	923	201	923	201	849	184
2524	$\mathbf{b_l}$	**0.68**	**0.69**	**0.63**	**0.68**	**0.69**	**0.70**	**0.64**	**0.59**	**0.66**	**0.58**	**0.63**	**0.57**	**0.62**
	s.e	0.02	0.03	0.02	0.02	0.03	0.03	0.05	0.02	0.03	0.02	0.03	0.02	0.03
	$\mathbf{b_k}$	**0.20**	**0.05**	**0.23**	**0.17**	**0.22**	**0.06**	0.02	**0.10**	**0.22**	**0.13**	**0.09**	**0.20**	**0.28**
	s.e.	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.04	0.02	0.03	0.04	0.04	0.02
	$\mathbf{b_a}$	**0.08**	**0.44**	0.04	**0.08**	**0.08**	**0.39**	**0.54**	-0.15	-0.04	**-0.24**	0.03	-0.09	-0.04
	s.e.	0.01	0.04	0.05	0.02	0.02	0.05	0.07	0.11	0.04	0.12	0.05	0.09	0.05
	R^2	0.74	0.66	0.98	0.69	0.74	0.63	0.57	0.98	0.98	0.98	0.98	0.98	0.98
	No	3907	3907	2578	2510	1397	2510	1397	1745	833	1745	833	1627	772
2661	$\mathbf{b_l}$	**0.72**	**0.76**	**0.68**	**0.79**	**0.66**	**0.70**	**0.80**	**1.11**	**0.58**	0.67	**0.52**	**0.78**	**0.46**
	s.e	0.04	0.06	0.05	0.12	0.04	0.16	0.07	0.18	0.05	0.37	0.06	0.35	0.07
	$\mathbf{b_k}$	**0.25**	0.06	**0.34**	0.17	**0.24**	0.08	0.05	**0.12**	0.05	**0.54**	**0.16**	**0.51**	**0.10**
	s.e.	0.03	0.04	0.02	0.10	0.03	0.13	0.04	0.02	0.07	0.06	0.06	0.06	0.04
	$\mathbf{b_a}$	0.05	**0.20**	-0.00	**0.18**	-0.02	0.33	**0.19**	-0.08	0.16	**0.89**	-0.00	0.24	0.01
	s.e.	0.03	0.08	0.05	0.07	0.03	0.17	0.09	0.05	0.22	0.17	0.02	0.18	0.01

	R^2	0.92	0.90	0.99	0.94	0.87	0.93	0.80	0.99	0.99	1.00	1.00	0.99	1.00
	No	373	373	232	105	268	105	268	64	168	64	168	60	154
2710	**b_l**	**0.61**	**0.50**	**0.50**	**0.69**	**0.54**	**0.63**	**0.30**	**0.56**	**0.43**	**0.59**	**0.39**	**0.60**	**0.43**
	s.e	0.04	0.04	0.05	0.05	0.05	0.06	0.06	0.07	0.05	0.07	0.06	0.08	0.07
	b_k	**0.24**	**0.10**	**0.27**	**0.12**	**0.33**	**0.08**	008	**0.20**	**0.37**	**0.16**	**0.23**	**0.14**	**0.37**
	s.e.	0.02	0.02	0.04	0.03	0.03	0.04	0.05	0.05	0.04	0.06	0.05	0.04	0.04
	b_a	**-0.13**	**0.32**	-0.06	**-0.10**	**-0.23**	0.17	**0.74**	-0.06	**-0.21**	-0.00	**-0.42**	**-0.23**	-0.05
	s.e.	0.03	0.11	0.09	0.04	0.05	0.14	0.16	0.19	0.10	0.01	0.08	0.10	0.10
	R^2	0.72	0.62	0.98	0.67	0.73	0.63	0.65	0.98	0.99	0.98	0.99	0.98	0.99
	No	927	927	601	519	408	519	408	351	250	351	250	333	234
2811	**b_l**	**0.74**	**0.89**	**0.66**	**0.73**	**0.72**	**0.92**	**0.84**	**0.61**	**0.66**	**0.61**	**0.65**	**0.62**	**0.63**
	s.e	0.02	0.05	0.03	0.04	0.03	0.06	0.08	0.04	0.04	0.04	0.04	0.05	0.04
	b_k	**0.13**	**0.05**	**0.27**	**0.09**	**0.18**	0.04	0.07	**0.09**	**0.20**	**0.07**	**0.24**	**0.18**	**0.16**
	s.e.	0.02	0.02	0.03	0.02	0.02	0.03	0.04	0.03	0.04	0.03	0.03	0.03	0.02
	b_a	**0.07**	**0.20**	-0.13	0.00	**0.12**	0.13	**0.29**	0.05	0.13	**0.21**	-0.02	-0.09	**0.29**
	s.e.	0.02	0.07	0.12	0.02	0.03	0.11	0.10	0.07	0.12	0.06	0.06	0.07	0.05
	R^2	0.75	0.74	0.97	0.71	0.76	0.70	0.75	0.98	0.98	0.98	0.98	0.98	0.98
	No	1762	1762	1116	937	825	937	825	644	472	644	472	610	446
2852	**b_l**	**0.73**	**0.58**	**0.74**	**0.70**	**0.76**	**0.56**	**0.64**	**0.65**	**0.78**	**0.66**	**0.77**	**0.66**	**0.73**
	s.e	0.01	0.02	0.02	0.02	0.02	0.03	0.04	0.02	0.02	0.02	0.02	0.02	0.02
	b_k	**0.16**	**0.07**	**0.15**	**0.14**	**0.15**	**0.06**	**0.08**	**0.12**	**0.08**	**0.10**	**0.06**	**0.11**	**0.20**
	s.e.	0.01	0.01	0.03	0.02	0.01	0.02	0.02	0.03	0.03	0.03	0.02	0.02	0.03
	b_a	-0.01	**0.19**	0.00	-0.01	-0.03	**0.13**	**0.26**	0.32	**0.47**	-0.16	**-0.11**	-0.01	**0.26**
	s.e.	0.01	0.04	0.16	0.02	0.02	0.06	0.06	0.21	0.19	0.09	0.04	0.06	0.10
	R^2	0.74	0.72	0.96	0.66	0.75	0.65	0.72	0.97	0.96	0.97	0.97	0.98	0.97
	No	5627	5627	3708	3161	2466	3161	2466	2236	1472	2236	1472	2077	1374
2875	**b_l**	**0.70**	**0.79**	**0.67**	**0.66**	**0.75**	**0.72**	**0.93**	**0.60**	**0.72**	**0.60**	**0.70**	**0.60**	**0.69**
	s.e	0.01	0.02	0.02	0.02	0.02	0.03	0.04	0.02	0.02	0.02	0.02	0.02	0.03
	b_k	**0.16**	**0.06**	**0.13**	**0.14**	**0.18**	**0.09**	0.02	**0.11**	**0.18**	**0.16**	**0.21**	**0.19**	**0.25**
	s.e.	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.04	0.02	0.04	0.03	0.03
	b_a	0.00	**0.18**	**-0.13**	**0.02**	**-0.05**	**0.16**	**0.21**	**-0.31**	-0.05	**0.14**	-0.00	**-0.15**	**0.12**
	s.e.	0.01	0.04	0.03	0.01	0.02	0.05	0.06	0.07	0.11	0.05	0.08	0.05	0.06
	R^2	0.73	0.71	0.97	0.68	0.71	0.67	0.67	0.98	0.97	0.98	0.97	0.98	0.98
	No	4816	4816	3216	2860	1956	2860	1956	2063	1153	2063	1153	1950	1099
2911	**b_l**	**0.90**	**0.92**	**0.75**	**1.04**	**0.53**	**0.93**	**0.49**	**0.94**	**0.45**				
	s.e	0.05	0.09	0.07	0.06	0.12	0.11	0.17	0.11	0.19				
	b_k	0.05	0.04	**0.18**	**0.08**	**0.27**	0.03	**0.19**	0.03	**0.22**				
	s.e.	0.04	0.05	0.02	0.04	0.06	0.07	0.08	0.03	0.06				
	b_a	0.07	-0.15	0.11	0.05	0.19	-0.28	0.56	0.15	0.13				
	s.e.	0.04	0.13	0.07	0.04	0.11	0.15	0.30	0.08	0.14				
	R^2	0.93	0.92	0.99	0.94	0.90	0.89	0.84	0.98	0.99				
	No	199	199	126	132	67	132	67	87	39				
2912	**b_l**	**0.80**	**0.67**	**0.80**	**0.76**	**0.82**	**0.66**	**0.46**	**0.71**	**0.82**	**0.73**	**0.77**	**0.75**	**0.61**
	s.e	0.03	0.04	0.04	0.03	0.06	0.04	0.15	0.04	0.08	0.04	0.08	0.05	0.08
	b_k	**0.04**	**0.11**	**0.09**	0.03	0.07	**0.14**	0.04	**0.08**	0.04	0.02	**0.20**	0.02	**0.15**
	s.e.	0.02	0.02	0.02	0.02	0.05	0.02	0.06	0.02	0.04	0.03	0.04	0.02	0.04
	b_a	**0.06**	-0.02	-0.03	**0.04**	0.07	0.04	-0.01	0.04	**-0.60**	**0.14**	**-0.41**	0.05	0.09
	s.e.	0.02	0.08	0.05	0.02	0.06	0.09	0.16	0.05	0.29	0.04	0.12	0.05	0.05
	R^2	0.77	0.77	0.97	0.76	0.77	0.76	0.76	0.98	0.96	0.98	0.98	0.98	0.99
	No	1241	1241	834	882	359	882	359	597	237	597	237	533	224
2922	**b_l**	**0.73**	**0.33**	**0.70**	**0.69**	**0.76**	**0.51**	**0.19**	**0.61**	**0.69**	**0.60**	**0.68**	**0.63**	**0.69**
	s.e	0.02	0.04	0.03	0.03	0.04	0.06	0.07	0.04	0.04	0.04	0.04	0.04	0.05
	b_k	**0.09**	**0.08**	**0.13**	**0.10**	**0.10**	**0.13**	0.06	**0.09**	**0.12**	0.04	**0.16**	**0.09**	**0.18**
	s.e.	0.02	0.02	0.04	0.02	0.02	0.03	0.04	0.02	0.02	0.05	0.03	0.03	0.02
	b_a	**0.06**	**0.15**	0.08	**0.11**	-0.02	**0.22**	0.09	**0.11**	0.06	0.18	-0.00	**0.22**	-0.02
	s.e.	0.02	0.07	0.12	0.03	0.04	0.08	0.11	0.05	0.11	0.14	0.00	0.09	0.05

	R^2	0.79	0.76	0.98	0.76	0.81	0.75	0.78	0.98	0.98	0.99	0.99	0.99	0.99
	No	1258	1258	857	739	519	739	519	515	342	515	342	482	312
2924	**b_l**	**0.81**	**0.54**	**0.71**	**0.81**	**0.82**	**0.51**	**0.67**	**0.73**	**0.75**	**0.71**	**0.74**	**0.68**	**0.79**
	s.e	0.02	0.04	0.03	0.03	0.04	0.05	0.08	0.04	0.06	0.04	0.06	0.04	0.08
	b_k	**0.11**	**0.10**	**0.16**	**0.09**	**0.14**	**0.11**	0.05	**0.19**	0.08	**0.17**	**0.19**	**0.10**	**0.08**
	s.e.	0.02	0.02	0.02	0.02	0.03	0.03	0.04	0.02	0.06	0.03	0.06	0.02	0.04
	b_a	-0.00	**0.41**	**0.37**	-0.04	0.07	**0.36**	**0.57**	-0.13	-0.05	0.07	-0.08	-0.00	**0.25**
	s.e.	0.02	0.08	0.09	0.03	0.04	0.10	0.11	0.07	0.11	0.08	0.07	0.00	0.06
	R^2	0.78	0.70	0.98	0.77	0.83	0.69	0.70	0.97	0.99	0.98	0.99	0.98	0.99
	No	1264	1264	859	937	327	937	327	670	189	670	189	624	177
2953	**b_l**	**0.68**	**0.76**	**0.66**	**0.60**	**0.82**	**0.74**	**0.86**	**0.68**	**1.45**				
	s.e	0.06	0.08	0.06	0.07	0.14	0.09	0.14	0.08	0.49				
	b_k	**0.18**	**0.21**	**0.20**	**0.16**	0.13	**0.26**	0.00	**0.12**	0.12				
	s.e.	0.05	0.07	0.09	0.06	0.11	0.08	0.06	0.03	0.09				
	b_a	0.05	**0.30**	0.02	0.09	-0.01	**0.42**	-0.04	**0.48**	**-0.88**				
	s.e.	0.05	0.15	0.43	0.05	0.12	0.20	0.11	0.05	0.38				
	R^2	0.80	0.79	0.99	0.70	0.91	0.68	0.90	0.99	0.99				
	No	294	294	187	223	71	223	71	149	38				
2971	**b_l**	**0.68**	**0.63**	**0.60**	**0.83**	**0.33**	**0.62**	**1.14**	**0.71**	**0.43**	**0.56**	0.27	**0.40**	**0.56**
	s.e	0.06	0.08	0.08	0.08	0.12	0.09	0.20	0.09	0.16	0.11	0.27	0.17	0.10
	b_k	**0.18**	**0.27**	**0.21**	0.07	**0.40**	**0.26**	**0.30**	**0.37**	**0.42**	**0.34**	**0.42**	**0.50**	**0.45**
	s.e.	0.04	0.08	0.05	0.05	0.08	0.09	0.14	0.06	0.02	0.05	0.04	0.05	0.06
	b_a	-0.03	-0.29	0.09	-0.06	-0.01	-0.26	-0.13	**0.40**	-0.30	**0.48**	-0.14	0.04	0.16
	s.e.	0.05	0.22	0.17	0.06	0.11	0.28	0.30	0.12	0.16	0.12	0.09	0.10	0.28
	R^2	0.77	0.76	0.98	0.73	0.80	0.71	0.78	0.97	1.00	0.98	0.99	0.99	0.99
	No	421	421	296	306	115	306	115	217	79	217	79	196	71
3002	**b_l**	**0.94**	**0.94**	**0.90**	**0.88**	**1.02**	**0.91**	**1.08**	**0.79**	**1.09**	**0.78**	**1.03**	**0.77**	**0.86**
	s.e	0.03	0.04	0.03	0.03	0.06	0.05	0.10	0.04	0.07	0.04	0.07	0.04	0.08
	b_k	**0.06**	**0.06**	**0.16**	**0.04**	**0.11**	**0.06**	0.05	**0.20**	**0.17**	**0.23**	**0.11**	**0.18**	**0.26**
	s.e.	0.02	0.03	0.01	0.02	0.04	0.03	0.06	0.05	0.03	0.05	0.03	0.05	0.04
	b_a	0.03	**0.48**	-0.13	0.07	0.01	**0.36**	**0.75**	-0.13	-0.12	0.01	-0.00	**1.06**	**0.31**
	s.e.	0.03	0.09	0.10	0.04	0.06	0.11	0.16	0.26	0.07	0.29	0.14	0.30	0.12
	R^2	0.80	0.77	0.96	0.77	0.81	0.77	0.76	0.97	0.93	0.97	0.95	0.98	0.97
	No	1671	1671	1123	1140	531	1140	531	806	317	806	317	749	298
3110	**b_l**	**0.61**	**0.42**	**0.52**	**0.44**	**0.86**	**0.35**	**0.52**	**0.27**	**0.86**	**0.28**	**0.86**	**0.42**	**0.86**
	s.e	0.04	0.05	0.04	0.04	0.06	0.06	0.09	0.05	0.07	0.05	0.07	0.06	0.10
	b_k	**0.26**	**0.18**	**0.24**	**0.33**	**0.15**	**0.24**	0.06	**0.37**	0.01	**0.34**	**0.05**	**0.27**	**0.08**
	s.e.	0.03	0.04	0.02	0.03	0.04	0.05	0.06	0.04	0.03	0.05	0.03	0.04	0.04
	b_a	**-0.10**	**0.45**	**-0.11**	**-0.07**	**-0.16**	**0.36**	**0.62**	**-0.17**	**-0.35**	-0.00	**-0.66**	**-0.19**	-0.00
	s.e.	0.03	0.10	0.05	0.03	0.06	0.12	0.18	0.08	0.08	0.10	0.10	0.07	0.03
	R^2	0.76	0.64	0.97	0.70	0.79	0.61	0.59	0.98	0.96	0.99	0.96	0.99	0.97
	No	986	986	674	680	306	680	306	481	193	481	193	459	182
3162	**b_l**	**0.66**	**0.58**	**0.65**	**0.63**	**0.71**	**0.59**	**0.60**	**0.55**	**0.76**	**0.55**	**0.74**	**0.55**	**0.72**
	s.e	0.02	0.02	0.02	0.02	0.02	0.03	0.05	0.02	0.03	0.02	0.03	0.02	0.03
	b_k	**0.19**	**0.12**	**0.09**	**0.17**	**0.20**	**0.10**	**0.17**	**0.10**	**0.08**	**0.15**	**0.13**	**0.22**	**0.16**
	s.e.	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.03	0.04	0.02	0.04
	b_a	-0.00	**0.27**	**0.29**	0.01	-0.04	**0.30**	**0.16**	**0.59**	**-0.28**	**0.65**	-0.11	-0.00	**-0.42**
	s.e.	0.01	0.04	0.10	0.02	0.03	0.05	0.07	0.16	0.07	0.10	0.08	0.00	0.11
	R^2	0.72	0.69	0.97	0.67	0.72	0.63	0.71	0.98	0.97	0.98	0.97	0.98	0.98
	No	4345	4345	2956	2987	1358	2987	1358	2132	824	2132	824	2000	763
3220	**b_l**	**0.72**	**0.80**	**0.70**	**0.65**	**0.87**	**0.81**	**0.79**	**0.66**	**0.60**	**0.63**	**0.63**	**0.68**	**0.63**
	s.e	0.05	0.07	0.06	0.06	0.09	0.08	0.14	0.07	0.11	0.07	0.12	0.08	0.13
	b_k	**0.19**	0.00	**0.17**	**0.20**	**0.21**	0.02	0.05	**0.19**	**0.16**	**0.40**	**0.40**	**0.32**	**0.16**
	s.e.	0.03	0.04	0.04	0.04	0.06	0.05	0.08	0.02	0.05	0.03	0.04	0.05	0.03
	b_a	-0.07	0.06	-0.05	**-0.08**	-0.03	0.05	0.16	-0.07	**0.19**	**0.31**	**0.16**	**0.52**	**0.87**
	s.e.	0.04	0.10	0.11	0.04	0.09	0.11	0.27	0.06	0.07	0.07	0.06	0.14	0.09

	R^2	0.74	0.73	0.97	0.72	0.73	0.70	0.71	0.85	0.98	0.98	0.98	0.98	0.99
	No	961	961	675	687	274	687	274	497	178	497	178	463	165
3320	$\mathbf{b_l}$	**0.85**	**0.78**	**0.81**	**0.87**	**0.79**	**0.86**	**0.48**	**0.84**	**0.82**	**0.84**	**0.77**	**0.81**	**0.83**
	s.e	0.02	0.03	0.02	0.02	0.04	0.04	0.07	0.03	0.05	0.03	0.05	0.03	0.05
	$\mathbf{b_k}$	**0.09**	**0.05**	**0.11**	**0.07**	**0.16**	**0.05**	**0.10**	**0.04**	**0.10**	**0.16**	**0.08**	**0.14**	**0.14**
	s.e.	0.09	0.02	0.02	0.02	0.03	0.02	0.04	0.02	0.02	0.03	0.04	0.03	0.05
	$\mathbf{b_a}$	**-0.07**	**0.25**	-0.05	**-0.07**	**-0.09**	**0.22**	**0.29**	0.00	**-0.48**	**-0.26**	**-0.40**	-0.17	-0.00
	s.e.	0.01	0.05	0.05	0.02	0.03	0.06	0.10	0.05	0.11	0.08	0.18	0.10	0.00
	R^2	0.75	0.71	0.97	0.74	0.76	0.71	0.67	0.96	0.97	0.97	0.98	0.97	0.98
	No	2934	2934	2008	2263	671	2263	671	1573	435	1573	435	1458	410
3410	$\mathbf{b_l}$	**0.74**	**0.58**	**0.62**	**0.66**	**0.84**	**0.65**	0.05	**0.45**	**0.74**	**0.51**	**0.73**	**0.61**	**0.75**
	s.e	0.05	0.11	0.06	0.06	0.08	0.11	0.29	0.08	0.09	0.08	0.09	0.10	0.12
	$\mathbf{b_k}$	**0.19**	**0.10**	**0.24**	**0.25**	**0.12**	0.02	**0.53**	**0.46**	0.02	**0.29**	**0.23**	**0.19**	**0.11**
	s.e.	0.03	0.05	0.02	0.04	0.05	0.06	0.13	0.06	0.04	0.02	0.09	0.03	0.05
	$\mathbf{b_a}$	**0.09**	0.14	**0.19**	0.08	0.07	-0.30	**0.54**	**-1.32**	-0.16	**0.19**	**-1.49**	0.01	**-1.42**
	s.e.	0.04	0.14	0.07	0.05	0.10	0.19	0.24	0.22	0.13	0.08	0.36	0.10	0.24
	R^2	0.84	0.84	0.98	0.84	0.80	0.76	0.68	0.99	0.97	0.99	0.98	0.99	0.99
	No	608	608	418	423	185	423	185	300	118	300	118	271	108
3430	$\mathbf{b_l}$	**0.90**	**0.82**	**0.78**	**0.93**	**0.84**	**0.60**	**1.50**	**0.74**	**0.68**	**0.75**	**0.60**	**0.65**	**0.70**
	s.e	0.04	0.06	0.05	0.05	0.07	0.07	0.09	0.06	0.09	0.06	0.10	0.07	0.12
	$\mathbf{b_k}$	0.01	0.06	0.01	0.02	0.03	0.02	**-0.24**	0.07	0.07	**0.10**	0.05	**0.10**	**0.13**
	s.e.	0.03	0.04	0.01	0.04	0.05	0.05	0.05	0.05	0.08	0.05	0.07	0.05	0.06
	$\mathbf{b_a}$	**0.10**	**0.44**	**0.08**	**0.12**	0.00	**0.43**	**0.45**	**0.50**	-0.60	-0.13	0.11	-0.15	0.01
	s.e.	0.03	0.09	0.02	0.03	0.05	0.10	0.16	0.09	0.46	0.08	0.21	0.10	0.05
	R^2	0.68	0.62	0.81	0.67	0.67	0.58	0.62	0.96	0.98	0.96	0.98	0.98	0.98
	No	1036	1036	674	749	287	749	287	492	182	492	182	425	169
3530	$\mathbf{b_l}$	**0.68**	**0.74**	**0.60**	**0.71**	**0.62**	**0.74**	**0.76**	**0.58**	**0.72**	**0.58**	**0.56**	**0.59**	**0.65**
	s.e	0.04	0.07	0.04	0.04	0.07	0.08	0.15	0.04	0.12	0.04	0.13	0.05	0.25
	$\mathbf{b_k}$	**0.23**	**0.11**	**0.18**	**0.20**	**0.28**	**0.11**	0.08	**0.22**	**0.21**	**0.19**	**0.30**	**0.23**	**0.32**
	s.e.	0.03	0.04	0.04	0.03	0.05	0.04	0.07	0.04	0.02	0.04	0.04	0.04	0.03
	$\mathbf{b_a}$	0.02	0.19	**0.87**	**0.06**	**-0.22**	0.21	0.15	0.15	-0.11	0.00	-0.16	0.00	**-0.39**
	s.e.	0.03	0.11	0.13	0.03	0.07	0.12	0.22	0.10	0.08	0.00	0.12	0.00	0.10
	R^2	0.84	0.82	0.98	0.80	0.87	0.79	0.84	0.99	0.98	0.99	0.99	0.99	0.99
	No	885	885	627	689	196	689	196	495	132	495	132	460	121
3663	$\mathbf{b_l}$	**0.74**	**0.71**	**0.71**	**0.73**	**0.74**	**0.76**	**0.64**	**0.67**	**0.72**	**0.68**	**0.70**	**0.69**	**0.70**
	s.e	0.01	0.02	0.01	0.01	0.02	0.02	0.04	0.02	0.02	0.02	0.02	0.02	0.02
	$\mathbf{b_k}$	**0.18**	**0.08**	**0.16**	**0.12**	**0.21**	**0.05**	**0.12**	**0.12**	**0.20**	**0.13**	**0.18**	**0.08**	**0.13**
	s.e.	0.01	0.01	0.02	0.01	0.01	0.01	0.02	0.03	0.02	0.02	0.03	0.02	0.03
	$\mathbf{b_a}$	**0.04**	**0.26**	-0.17	0.00	**0.04**	**0.25**	**0.30**	0.01	0.05	**-0.10**	0.00	**-0.10**	0.08
	s.e.	0.01	0.03	0.09	0.01	0.02	0.04	0.06	0.13	0.07	0.05	0.00	0.05	0.08
	R^2	0.75	0.72	0.97	0.69	0.76	0.65	0.72	0.98	0.97	0.98	0.97	0.98	0.97
	No	7547	7547	4974	4708	2839	4708	2839	3310	1664	3310	1664	3080	1525

Notes: Reported R^2 in columns (4), (8) and (9) is the overall R^2. Numbers of observations in columns (5) and from (10) to (15) are from the last step of the OP estimator. E denotes exporting company and NE – non-exporting company. OP2, OP3, and OP4 denote the Olley-Pakes 2-step, 3-step, and 4-step algorithms, respectively.

Institute for International Integration Studies
The Sutherland Centre, Trinity College Dublin, Dublin 2, Ireland