THE UNIVERSITY of York

Discussion Papers in Economics

No. 12/18

International Trade and Productivity: Does Destination Matter?

Yevgeniya Shevtsova

Department of Economics and Related Studies
University of York
Heslington
York, YO10 5DD

International Trade and Productivity: Does Destination Matter?[1]

Yevgeniya Shevtsova [2]

Abstract

The paper empirically assesses microeconomic exporting-productivity nexus using the data for Ukrainian manufacturing and service sectors for the years 2000-2005. The results of the estimation show that firms with higher total factor productivity (TFP) levels in the period prior to entry are much more likely to enter export markets. Also age, size and intangible assets of the firm have significant positive influence on the probability of exporting. The results also suggest significant positive post-entry productivity effect for the firms that enter export markets and negative productivity effect for those that exit. At the industry level the results also confirm the presence of learning-by-exporting effect. However the effect is not universal and varies between different types of exporting firms and export destinations. Firms that export to the countries of the European Union and other OECD countries experience higher advances in their TFP than firms exporting to other CIS countries. The magnitude of the effect is also positively correlated with the capital intensity of the industries. These findings have important implications for the formation of industrial policies, suggesting that government programs designed to upgrade firms' productivity and innovative capabilities would increase the ability of domestic firms to overcome foreign market barriers as well as assimilate further benefits arising from exporting, which can further enhance international competitiveness of Ukrainian firms.

JEL codes: D24; F14; L25; R38

Keywords: exports; TFP; matching; Heckman procedure; system GMM; sample selection; endogeneity

[1] I would like to thank David Brown, Richard Harris, Mark Schaffer, Peter Simmons and Paul Hare for their valuable comments and help. All remaining errors are the responsibility of the author.

[2] University of York, York, YO10 5DD, UK; E-mail: eugenia.shevtsova@york.ac.uk

Introduction

An increasing number of studies on the exporting-productivity links suggests a number of ways by which engaging in international trade could be beneficial to the firm as well as aggregate productivity growth. In particular, the literature suggests two main effects. The first one is a *self-selection* hypothesis which presumes that, on average, potential exporters have higher productivity prior to entry as compared to firms that remain purely domestic. This hypothesis is supported by the substantial factual evidence of differences in characteristics between exporting and non-exporting firms. Stylized facts from a number of countries suggest that, on average, exporting firms are more productive and more capital intensive; they pay higher wages and have larger scale of operation. The reasons of a relatively better performance in the case of export-oriented firms are easy to derive. First of all, entrance to and successful operation in the export market depends upon the ability of the firm to face and successfully overcome significant competition with foreign rivals. Another reason of a better exporter's performance is the existence of sunk-entry costs, which include the costs of marketing, distribution, establishing foreign networks and others. This means that potential exporters have to be more productive than their domestic rivals to afford the fixed costs of entering a foreign market.

An alternative, but not excluding, is a *learning-by-exporting* hypothesis, which means that those firms which manage to engage in exporting benefit from further advances in their productivity even after the entry took place. The reasons for this include access to the new, better technologies, product designs, technical and managerial expertise, which, together with economies of scale, contribute to the overall improvement of the manufacturing process. Furthermore, higher intensity of the foreign market competition also provides a productivity boost to the new exporters. However, this proposition has not been as widely confirmed by the results of empirical as well as theoretical studies.

The theoretical models developed by Melitz (2003), Bernard *et al.* (2003) and Clerides *et. al.* (1998) provide theoretical evidence that firms have to be more productive to overcome sunk costs and enter global markets. A simple model by Lopez (2004) shows that one of the possible explanations of the self-selection pattern is conscious attempts of firms to increase their productivity (via investment in R&D activities and new technologies), with the explicit purpose of becoming an exporter. This idea was further developed by Hallward-Driemeier, Iarossi and Sokoloff (2002), who did not limit the discussion to more productive firms, but instead tried to show that firms target export markets from the initial date of operation, and design their investment decisions and technology activities in a way that will allow them to increase their productivity.

Following theoretical developments, recent empirical research has provided strong empirical evidence in favour of the self-selection hypothesis, confirming the existence of significant productivity differences between exporting and non-exporting establishments. Aw and Hwang (1995) find significant differences in size and productivity levels between exporters and non-exporters in Taiwanese electronic industry. Bernard and Jensen (1999) confirm the same results for US manufacturing; Girma *et al.* (2004), Greenaway and Kneller (2004), Harris and Li (2007) – find the same relationship for the UK manufacturing and service firms, Baldwin and Gu (2004) - for Canadian manufacturing firms, and Clerides, Lack and Tybout (1998) – for Columbia, Mexico and Morocco; Bernard and Wagner (1997) – for German manufacturing firms; Delgado, Farinas and Ruano (2002) – for Spanish manufacturing firms. There are, however, some studies that fail to find any significant productivity differences between exporters and non-exporters. This conclusion appears mostly in the papers that study micro-level data from the advanced, developed countries with stable, non-increasing, export shares. Greenaway et. al. (2005), for example, found little difference in the efficiency between exporters and non-exporters for Swedish manufacturers that have a relatively high average level of international exposure. Bleaney and Wakelin (2002) found that non-innovating firms are more likely to export having lower unit labour costs instead of higher levels of productivity, while innovating firms have a higher probability of exporting when they have accumulated a higher number of innovations. Finally, Damijan *et. al.* (2005) in his study on Slovenian firms show that on average higher productivity is required only for firms that start exporting to advanced markets and not for the firms that target developing countries.

Empirical evidence in favour of learning-by-exporting hypothesis is, however, much more scarce. A number of empirical studies failed to find any significant impact of exporting on productivity levels in the post-entry period, with the majority of findings being that firms on average have significantly higher growth levels in terms of employment and wages after entering export markets (Bernard and Jensen 1999, 2004c; Bernard and Wagner, 1997). However, with the development of new econometric techniques some positive effects of learning-by-exporting have been identified, especially in cases of developing countries (Castellani, 2002; Hallward-Driemier *et al.*, 2002; Blalock and Gertler, 2004; Fernandes and Isgut, 2005; Yasar and Rejesus, 2005).

Furthermore, several studies have found evidence in favour of both self-selection and learning-by-exporting effects (Baldwin and Gu, 2003; Girma *et al.*, 2004; Greaway and Yu, 2004; Harris and Li, 2007).

Such a wide range of empirical results is caused by a number of reasons. First of all, depending on the country of interest, similar analysis may lead to completely different results depending on the market size, intensity of domestic competition and levels of R&D investment. Furthermore, the amount of productivity gains coming from exporting depends to a high extent on the characteristics of specific export markets. Blalock and Gertler (2004) and Damijan *et al.* (2004)

argue that significant productivity gains arise only when exporting is targeted at the advanced export markets, while exporting to the markets of similar levels of economic development leads to small or even insignificant productivity gains. This conclusion is supported by the results of empirical studies that find evidence in favour of the learning-by-exporting hypothesis using the data from developing countries with increasing export shares, changes in the export structure, and low technological frontiers. At the same time much less support has been found in cases of developed countries with stable export shares and considerable technological advances.

In the current paper I confirm some of the theoretical conclusions and empirical evidence discussed above as well as provide some new insights. In particular, this paper has an advantage of using a census of Ukrainian manufacturing and service firms for the period 2000-2005 that allows us to distinguish between firms' operations in different export markets. I start with reaffirming self-selection hypothesis. The results, in line with the majority of recent empirical evidence, show that Ukrainian exporters are more productive prior to entry into overseas markets. Also age, size and intangible assets of the firm have significant positive influence on the probability of exporting. Furthermore, I confirm the significance of the post-entry learning-by-exporting effect. However, the results are not universal and depend on the type of industry and the foreign market served. In particular, we observe significant productivity gains in case of capital-intensive industries; while in case of labour-intensive industries learning-by-exporting effect is minor and often insignificant. The results are also much more pronounced in case of serving more competitive, advanced export markets.

In the next section I describe the main features of the dataset used in the analysis and provide evidence on the productivity differences between exporting and non-exporting firms. Section three provides a brief description of the methodology used for the empirical analysis and a short discussion of estimation techniques. Section four presents the results of the estimation of the self-selection and learning-by-exporting hypotheses at the industry level distinguishing between different export markets. The final section provides policy implications and concludes.

Data and Descriptive Statistics

The main contribution of the current paper to the existing literature is the possibility to study time and spatial patterns of export-productivity links. In particular, the paper uses the dataset which groups consolidated annual accounts data on the population of Ukrainian manufacturing and service firms. All firms are uniquely defined by their VAT (OKPO) number and divided into sectors according to the Ukrainian Office of National Statistics (Derjkomstat) nomenclature, which is comparable to the NACE[3] classification[4].

[3] The NACE Revue 1 classification can be downloaded from the Eurostat Ramon server: http://ec.europa.euostat/ramon/nomenclatures/
[4] The sectors are further grouped so that they correspond to the NACE classification.

The data contains basic information on firm-specific characteristics, such as employment, output, sales, assets, 2-digit industry code, different types of intermediate expenditures (including R&D and innovation expenditure), investment and age of the firm. The data have been compiled from the National Institute of Statistics, checked and cleaned for consistency. Furthermore, the dataset contains detailed information on trade flows for Ukrainian firms with all countries. Such detailed data is rarely available for empirical analysis. Damijan *et. al*. (2005) explores exporting-productivity nexus using aggregate-level export data by the country of destination. The authors, however, do not distinguish between different industries in their empirical exercise. Using current data, however, should enable us to explore whether different export markets require different productivity levels for the new entrants and see if the results differ in different industries.

The final dataset used for statistical analysis comprises an unbalanced panel of firms in 22 industries based on the 2-digit NACE industry code, with 337,057 firms and 1,077,292 observations covering the period 2000-2005, with information showing entry and exit from export markets[5]. Table 1 shows that the average annual number of firms in the sample is 179, 432, while the average annual percent of exporting firms in the sample is 5.6%.

Table 1. Number of firms, share of exporter (%) by year, 2000-2005

Year	**2000**	**2002**	**2003**	**2005**	**Average**
Number of firms	138,171	186,578	191,760	184,829	179,432
Number of exporters	8,694	10,307	10,848	8,005	9,909
Share of exporters, %	6.3%	5.5%	5.7%	4.3%	5.6%

Note: Database used in the analysis

Table 2 contains summary statistics for the basic variables - output, capital, employment and material costs - for selected years. The statistics reflects increasing output and material expenditure and declining average employment size and capital that is caused by the increasing number of small and medium market entrants.

Table 2. Means (standard deviation) of production function variables (2000, 2003, 2005)

	2000	**2003**	**2005**
Output (Value added)	1692.248 (43923.67)	2061.05 (51019.31)	5303.714 (124614.1)
Employment	54.51899 (762.04)	37.77886 (646.03)	24.62973 (429.79)
Materials	3648.21 (49598.52)	6348.605 (79180.38)	5974.771 (107172.1)
Capital	3097.747 (60613.25)	2467.321 (53056.17)	1858.925 (33621.67)

Note: Capital, materials and output are expressed in constant 2000 prices, thousands of UAH.

[5] Appendix 1 contains summary statistics on the number and the percent of exporting firms by industry

The sample statistics might cause a concern that large firms might be over-represented in the sample (as in case of the Annual Respondents Database (ARD) in the UK). However, according to the Enterprise Survey data collected by the World Bank Group[6] Ukrainian firms are among the largest in the Eastern European and Central Asian (ECA) region in terms of permanent and temporary workforce. In particular, the survey reports that Ukrainian firms have the sixth largest permanent workforce in the ECA region. The average firm in Ukraine employs 56.8 permanent workers, while average ECA firm employs only 44.0 workers, and an average EU-10 firm – only 37.3 workers. Moreover, firms in manufacturing are more than twice as large as those in retail and other services. And majority of exporters are at least double the size of non-exporters.

For the empirical analysis, we use firms of the 6 manufacturing sectors and 3 service sectors. The sectors have been chosen due to the relatively high shares of exporting firms. Producer price indices used to deflate firm-level sales as well as material inputs and investments are available from the Ukraine State Statistic Committee[7] website.

First, we follow the exercise used by Girma et al. (2005), Wagner (2006) and Harris and Li (2007) to test the rank ordering of the total factor productivity (TFP) distribution of exporting versus non-exporting firms8. Table 3 shows that in most of the industries TFP distribution of exporters dominates that of non-exporters. Only in some industries there is an evidence of some cross-over between the two sub-groups (Figure 1). However, this feature is observed for the industries that specialize mainly in the exports of resources and products of low levels of processing. Hence, one can speculate that the trade advantage for the firms in these industries depends on access to natural resources, but not on the TFP *per se*.

Table 3. Two-sample Kolmogorov-Smirnov tests on the distribution of TFP by various subgroups and industries, Ukraine, 2000-2005

NACE code	Industry	All exporters	All non-exporters
(A/B)	Agriculture/forestry/fishing	-0.275***	0.101***
(CA)	Mining/quarrying of energy producing materials	-0.003	0.279***
(CB)	Mining/quarrying, except of energy producing materials	-0.002	0.388***
(DA)	Food/beverages/tobacco	-0.003	0.085***
(DB/DC)	Textile/clothing/leather/fur	-0.005	0.086***
(DD)	Wood/wood products (+36)	-0.018	0.126***
(DE)	Paper/printing/publishing	-0.012	0.234***
(DF/DG)	Coke/nuclear/chemical	-0.091***	0.101***
(DH)	Rubber/plastic	-0.025	0.117***
(DI)	Non-metallic minerals	-0.068***	0.091***
(DJ)	Basic/fabricated metals	-0.009	0.181***
(DK)	Machinery and equipment	-0.053***	0.057***
(DL)	Electrical and optical equipment	-0.032	0.126***

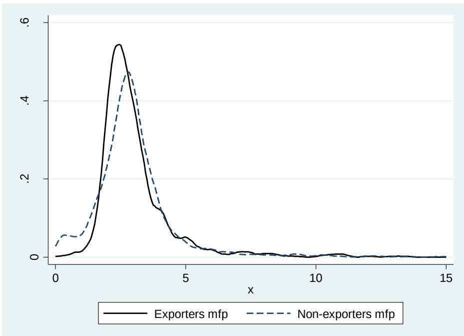
[6] http://www.enterprisesurveys.org/; The survey was conducted between June and August 2008 and included 851 firms.
[7] Ukrainian State Statistic Committee website: http://www.ukrstat.gov.ua/
[8] The analysis is based on the TFP estimated in section 0.

(DM)	Transport equipment	-0.101 ***	0.024***
(DN)	Manufacturing n.e.c.	-0.006	0.428***
(E)	Electricity, gas and water supply	-0.000	0.620***
(G pt1)	Wholesale	-0.001	0.266***
(G pt2)	Retail trade	-0.004	0.208***
(G pt3)	Repair of motor vehicles	-0.023	0.103***
(H)	Hotels/restaurants	-0.003	0.319***
(K)	Real estate/renting/business activities	-0.001	0.248***
(L)	Public administration and defence	-0.212	0.516***
(O)	Community/social/personal service activities	-0.002	0.535***
(I)	Transport/transport services/post	-0.001	0.374***

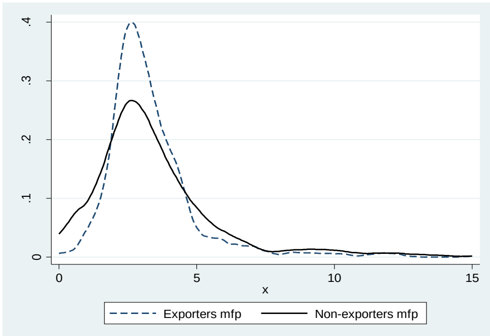
Note: H_0: Distribution of non-exporters' TFP dominates that of exporters
H_1: Distribution of exporters' TFP dominates that of non-exporters
***- denotes null rejected at 1% level; **- denotes null rejected at 5% level; *- denotes null rejected at 10% level

Figure 1. Productivity-level differences between exporters and non-exporters in Various Industries.

Kernel density distribution : Agriculture/forestry/fishing



Kernel density distribution : Machinery and equipment



Source : Own calculations

Total Factor Productivity Estimation

Usually the studies on productivity on the firm level assume the production function (measured as deflated sales, gross output or value added) to be a function of inputs and productivity of the firm. The standard approach to measure TFP implies estimating production function using equation (5.1) to obtain the elasticities of output with respect to inputs.

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

In equation (5.1) *y, e, m* and *k* stand for the logarithms of output, employment, intermediate inputs and capital stock in firm *i* at time *t*. Furthermore, α_0 is a mean efficiency level across firms and over time and u_{it} is a time- and producer-specific deviation from the mean value (Van Beveren, 2010). Following the standard approach the TFP is calculated in two steps. The first step estimates elasticities of output with respect to inputs ($\alpha_e, \alpha_m, \alpha_k$). And the second step obtains TFP as sum of the residual from the equation (1) and the time trend *t*:

$$\ln T\hat{F}P_{it} = \hat{\alpha}_t t + \hat{u}_{it} = y_{it} - \hat{\alpha}_e e_{it} - \hat{\alpha}_m m_{it} - \hat{\alpha}_k k_{it} \tag{2}$$

However, u_{it} can further be decomposed into two components; and one of them is observable (or at least predictable) for the firm. Thus, equation (1) transforms into:

$$y_{it} = \alpha_0 + \alpha_E e_{it} + \alpha_M m_{it} + \alpha_K k_{it} + \alpha_T t + \omega_{it} + \varepsilon_{it} \tag{3}$$

Where $\alpha_0 + \omega_{it} = w_{it}$ stands for the firm-level unobserved productivity, which is not observable to the researcher, but observable for the firm. And ε_{it} is an i.i.d. error component. Intuitively w_{it} might be associated with such variables as managerial ability of the firm, break in production process due to equipment failures; expected defect rates in manufactured goods or expected amount of rainfall; while ε_{it} represents unexpected deviation from the expected levels of all the factors mentioned earlier.

Then according to the standard two-stage approach we can measure TFP as a sum of the residual obtained from equation (1) and the time trend representing technological progress.

$$\ln T\dot{F}P_{it} = \hat{\alpha}_T + \hat{\alpha}_\omega \dot{\omega}_{it} \equiv \dot{y}_{it} - \hat{\alpha}_e \dot{e}_{it} - \hat{\alpha}_e \dot{m}_{it} - \hat{\alpha}_e \dot{k}_{it} \tag{4}$$

The TFP measures obtained in the first stage are further regressed against a range of TFP determinants, such as export status, age, intangible assets and others. However, since those variables were omitted from equations (1) – (3) and consequently assumed to be random, they automatically became a part of an error term (u_{it}), used to obtain the estimates of the TFP. Thus, when we use measures of TFP obtained through the two-stage approach to model TFP determinants, we are likely to get inefficient and biased estimates of the second-stage model parameters (Newey and McFadden, 1999, Wang and Schmidt, 2002, and Harris, 2005).

In order to avoid biased results we include all the potential output and TFP determinants in the equation (5.1)[9] that is further estimated using system-GMM approach to allow for the use of fixed effects and endogenous inputs. This way we address the *problem of inefficiency* and *omitted variable bias* at the same time testing the significance of all output and TFP determinants (including export status) directly[10].

[9] Harris (2005); Van Beveren (2007); Ackelberg *et al.* (2010) provide a detailed discussion of the methodological issues related the estimation of TFP. Please refer to their works for a more detailed discussion.

[10] Please refer to Shevtsova (2010) for the comparison of different TFP estimation techniques with the use of current data.

Exporting-Productivity Nexus

Theoretical background

Estimating exporting-productivity links on the micro level may be complicated by such methodological difficulties as *endogeneity* and *selection bias*. Selection bias occurs because firms that become exporters may be systematically different from their domestic counterparts in certain unobservable characteristics which make them superior to non-exporting firms even if they remained purely domestic, thus affecting their decision to engage into exporting. Hence a simple comparison of average productivities between exporters and non-exporters may result in biased estimates of the treatment effect[11]. Furthermore, firm's decision to export might be correlated with its unobserved productivity component, giving rise to the endogeneity problem.

There are several standard techniques that address endogeneity and sample selection bias. The first approach that deals with selection bias is *instrumental variables* (IV) estimation. This method requires finding appropriate instrument variables that affect the treatment decision (decision to export) but do not directly influence the outcome (TFP). In this case such variables can be used to overcome the problem of self-selection. In other words instrumental variable affects the outcome (TFP) indirectly through its impact on the treatment participation (exporting). However, it does not enter into the outcome equation directly. Hence, such a variable can be used to eliminate the problem of self-selection and identify the causal impact of treatment participation on the outcome. The main problem with the IV approach is availability of appropriate instruments, which sometimes might be limited due to data issues and economic mechanisms that determine the relationship between treatment and outcome (Angrist and Krueger, 2001). Second problem with IV approach is related to heterogeneity of treatment effects. In such case, instead of estimating an average impact of treatment effect on treated, the IV model will estimate a Local Average Treatment Effect (LATE). In which case, we will get estimates of the local impact of the instrument variable on those participants who change their participation status in response to a change in the instrument variable value (Angrist and Imbens, 1995; Heckman 2000). This might result in different impacts for different instruments instead of the homogenous treatment effect, especially in cases when the data is characterised by a high degree of heterogeneity. Previously used instruments in this case include age of the firm and its intangible assets (Harris and Li, 2007; Damijan *et. al.*, 2005). Previous empirical evidence suggests that these variables have no significant impact of the real gross output. However, they are usually highly significant determinants of the export status (Harris and Li, 2007). Thus, following Harris and Li (2007) I estimate the following dynamic panel data (DPD) production function additionally including the age of the firm and the dummy for intangible assets as instruments:

[11] See Heckman and Navarro-Lozano (2004) for a formal discussion.

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

In equation (5) Y is real gross output, x_1 represents the logarithm of intermediate inputs; x_2 –the logarithm of capital stock; x_3 the logarithm of total employment; x_4 time trend to take account of technical progress; D_l is a set of dummy variables indicating export status, including exp_never, exp_entry , exp_exit , exp_both[12] ; Reg_n and Ind_F are region and industry dummy variables respectively. The composite error term has three elements: η_i affecting all observation for the cross-section firm i; t_t affects all firms for period t; and e_{it} affects only firm i during period t.

To take an account of the potential endogeneity problem equation (5) is estimated using Generalized Method of Moments (GMM) systems approach available in STATA 9-12, which can account for both endogenous regressors[13] and a first-order autoregressive term.

The second approach used to deal with self-selection bias is a standard Heckman two-stage (or control function) procedure, which is closely linked to the IV approach. First, predicted values of the probability of exporting are obtained with the help of the first-stage probit (logit) estimator. These predicted values are further used to calculate inverse Mills ratios (sample selectivity correction terms), which are included in the second-stage equation to control for correlation between firm's productivity and its export decision. That is, if $\hat{P}_{it}$ is the predicted propensity score of exporting of the firm i at time t (see Equation(7)), then the inverse Mills ratios (or selectivity terms) are given by:

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

One of the limitations of Heckman procedure is the requirement for the *correct* specification of the first-stage nonlinear regression. If probit (logit) is used to generate fitted values that are further plugged into the second-stage linear regression the estimates of the second-stage will only be consistent in case, if the specification of the first-stage nonlinear model is perfectly *correct*, which raises the risk of specification error (Angrist and Krueger, 2001). Also, as noted

[12] I follow Harris and Li (2007) and divide firms into five sub-groups according to their export status: those that always exported, those that never exported, those that entered into exporting, those that exited and lastly, those that started and then stopped exporting more than once.

[13] This is done through the use of appropriate instruments involving lagged values – in both values and first differences – of the potentially endogenous variables in the model.

by Puhani (2000), Heckman procedure can often lead to non-robust results due to collinearity problems.

At last, one of the most commonly used methods to tackle self-selection is matching. This technique implies matching every exporting firm with a domestically oriented firm that possesses very similar characteristics. Thus, this technique allows us to construct a matched sample of non-exporting firms with the same observable characteristics that influence their productivity, hence the probability of exporting. This matched sample provides us with missing information on the outcomes which exporters would have experienced if they remained purely domestic. One methodological difficulty of matching is that some differences in unobservable characteristics may still be present between the treatment and control group. However, since matching is done on a common set of variables (the ones that impact the outcome and the ones that impact on participation in the treatment); this method assumes that any selection of unobservables has no influence on the outcomes in the absence of treatment (Harris, 2005). Furthermore, as discussed in Heckman and Navarro-Lozano (2004), excess information about treatment participation might sometimes lead to perfect prediction of treatment probability, which will make it impossible to implement matching on a common set of variables. Another problem of this approach is the requirement for a large dataset which includes all variables that impact selection into treatment as well as outcomes (Heckman and Navarro-Lozano, 2004; Harris, 2005). Moreover, treated firms, for which there is no match in the untreated sub-group are usually dropped, which can significantly reduce the size of the treated sub-group in the analysis. Thus, matching works only in case when there is enough common support between treated and untreated (control) sub-group. Finally, one of the assumptions of matching is that the effect for the average treatment participant equals to the effect for the marginal participant[14], which is an unattractive implication according to Heckman and Navarro-Lozano (2004).

This paper implements *all three approaches discussed above* starting with estimating the following (random effects panel) probit model to identify the probability of becoming exporter (i. e. the propensity score):

$$P(Export_{it}=1)= \phi(\ln LP_{it-1}, \ln Age_{it-1}, Intang_{it-1}, \ln Emp_{it-1}, (\ln Emp_{it-1})^2, Industry_{it}, \mathrm{Re}gion_{it}, Year_t) \tag{7}$$

Where *Export* is coded 1 if the firm exported at any time during 2000-2005; *LP* is the estimate of the Labour Productivity; *Age* is the age of the firm; *Intang* is coded 1 if the firm has nonzero intangible assets[15] (the average annual percent of firms possessing positive intangible assets equals 14.8%; we assume that the rest of the sample does not possess any intangible assets by

[14] In other words the effect of treatment on the treated is the same as unconditional treatment effect.

[15] The non-monetary assets may refer to patents, copyrights, trademarks, innovative activities, advertising, goodwill, brand recognition and similar intangible assets. Since there is considerable controversy about what should be included and how to measure intangible assets, I follow Harris and Li (2007) and use a dummy variable to measure intangible assets.

setting the rest of the observations to zero), *Emp* represents the number of employees; and *Industry*, *Region and Year* are dummy variables indicating each industry subgroup, regional attribute and year. The model is also estimated separately for each of the nine sectors, which also allows us to exclude industry specific dummies from the regression.

I then use the propensity scores (probability of exporting) to construct the matched sample (Girma *et al.*, 2004). In order to increase the quality of matching, I require potential matches to be in the same 2-digit NACE industry as their exporting counterparts. The matched comparison group is constructed using the "nearest-neighbour" approach with replacement. Having obtained the matched sample, the learning-by-exporting hypothesis is tested by re-estimating the dynamic panel data model given in equation (5) using the matched data.

The current paper uses instrumental variables to test the impact of exporting on productivity. Heckman and propensity score matching techniques are further adopted to test the robustness of our results. To the best of our knowledge, there are very few studies that implemented IV approach to test learning-by-exporting effect (Harris and Li, 2007; Damijan et. al., 2005) and only one study that explored learning-by-exporting effect, distinguishing between different export markets (Damijan et. al., 2005).

Results

I start with estimating Equation (7) using the probit model to test self-selection hypothesis and get the probability of exporting (propensity score) that will be used in the matching procedure at a later stage. The results of the eighteen industry groups are reported in Table 4. Overall, the results of the estimation show that size of the firm matters for exporting: i.e. larger firms are more likely to engage into exporting activity. Also firms with higher labour productivity in period *t-1* are more likely to enter export markets in period *t*[16]. Firms with positive intangible assets are more likely to enter export markets. On average intangible assets increase the likelihood of exporting by 12%. The effect is, however, not universal; and is proportional to the capital intensity of the industry. For example, industries like mining and agriculture experience show a relatively low impact of intangible assets on the probability of exporting. While for such industries as transport, electrical and optical equipment and fabricated metals possession of intangibles can increase the probability of exporting by 16% to 29%. Finally, in majority of the industries lagged age of a firm also increases the probability of exporting. Thus, the analysis in line with the majority of previous studies shows that there was a strong self-selection into export markets among Ukrainian firms during 2000-2005, in most of the eighteen industry sub-groups examined.

[16] Probability of exporting was estimated using labour productivity instead of the TFP due to the fact, that the results of the probit model were further used in the estimation of the production function with Heckman procedure.

The long-run estimates of the parameters indicating "learning-by-exporting" effect along with diagnostic tests for the ten industry sub-groups[17] that were selected to represent labour-intensive industries (agriculture/forestry/fishing; mining/quarrying; food/beverage/tobacco; textile/clothing/leather/fur); capital-intensive industries (machinery and equipment; electrical and optical equipment; manufacturing n.e.c.) and service sectors (wholesale trade; retail trade; transport/transport services and post) are shown in Table 5. The full set of results is not reported here due the space constraints. As discussed, age and intangible assets were included in the instrument set for the production function estimation using the IV approach; as these variables appear to be significant determinants of exporting, while producing insignificant estimates when included in the production function. The second approach is labelled "Heckman" in the results and includes selectivity correction terms λ_{0it} and λ_{1it} in the estimation of the equation (5). The last section of Table 5 ('Matching') features the results of the 'matched sample' estimation. The matched sample was constructed using the estimates of the probability of exporting (i. e. propensity score) from equation (7) in the "nearest-neighbour" matching approach with replacement. For most of the industry sub-groups the model shows no significant second order autocorrelation (AR(1) and AR(2)) and passes Hansen test, indicating the adequacy of the instrument set applied. In order to ensure the balancing of the regressors in a matched sample I use '*ptest*' (Leuven and Sianesi, 2003), which shows 100% bias reduction with respect to the values of propensity scores in the matched sample for all the industry sub-groups.

The results show that 'learning-by-exporting' effect is present, but not universal across the industries, which is consistent with other findings in the area. For example, Harris and Li (2007) found 'a fairly substantial post-entry productivity effect for the firms that are new to exporting', they also show significant long-run productivity losses for the firms that seize exporting; finally the firms that change their export status experience positive productivity gains while exporting. Furthermore, other studies that used developing countries data found relatively stronger support in favour of both self-selection and learning-by-exporting effects. One of the reasons for that being that technological differences and hence opportunities for acquiring and adopting new technologies during exporting activity are higher in case when trade occurs between developing and industrialised countries. Some examples include studies by Clerides et al. (1998) for Columbia, Morocco and Mexico; Castellani (2002) - for Italy; Hallward-Driemier (2002) *et al.* - for East Asia; Blalock and Gertler (2004) - for Indonesia; Fernandes and Isgut (2005) - for Colombia; Yasar and Rejesus (2005) – for Turkey.

The results presented in Table 5 are broadly similar for all three techniques used, with the results of the 'matched sample' estimation being slightly worse in terms of significance due to the reduced number of observations. Selectivity correction terms are insignificant in the

[17] For the full set of results of results, please refer to:

majority of industry sub-groups, indicating that IV approach has effectively controlled for sample-selection. In terms or the parameters, there are three sets of estimates that capture the impact of exporting on productivity. The fist one is *Exp_entry* variables that according to our hypothesis should deliver significant positive estimates for the first time entrants in period *t* and *t+1*. The second set includes *Exp_exit* variables that should potentially have significant negative estimates in *t-1*, *t* and *t+1*. Finally, the effect of exporting on TFP for the firms that change their export status more than once is captured by the set of *Exp_both* variables, that should potentially deliver significant positive estimates in periods *t* and *t+1*. To summarise the results, we calculate the weighted average across 18 industries using all the parameter estimates significant on the 15% level or less weighted by their shares in the real gross output (Table 7). The second column of Table 7 presents the results for the manufacturing sectors only[18].

A simple analysis of the results reveals that 'learning-by-exporting' effect is prevalent in the capital intensive industries, such as machinery and equipment (DK), electrical and optical equipment (DL) and other manufacturing (DN). The results for these industries show significant post-entry productivity boost for the first time entrants as well for the switching firms; and negative productivity effect for the firms that leaver export markets. However, in case of labour-intensive industries, such as mining (CB), agriculture/forestry/fishing (A/B), food/beverage/tobacco (DA) and textile/leather/fur (DB/DC) and service sectors (such as wholesale (G1) and retail trade (G2) and transport services and post (I)) we observe no significant long-run productivity effect of exporting. Furthermore, in many cases we observe positive productivity effect prior (period *t-1*) and after (period *t*) the exit from exporting. This might mean that, having absorbed better foreign technologies or managerial practices, firms switching back to domestic distribution find themselves more productive in a less competitive environment. Furthermore, across all industry sub-groups we can observe a negative productivity effect in the period prior to entry into exporting, which might be caused by the sunk costs that most of the firms undertake prior to entry into export markets. Results for the whole economy, presented in Table 7, show significant post-entry productivity boost for the new entrants: 18% long-run TFP increase in the year of entry and 11% in the year following entry. Firms that seize exporting experience negative productivity effect in the year prior to exit (-4%) and the year of exit (-25%) from exporting, which is followed by a subsequent 7% TFP increase. Finally the firms that change their export status o average experience a negative productivity shock in the entry year (-8%) followed by a subsequent TFP increase by 14%.

Furthermore, in order to study the role of export destination in the 'learning-by-exporting' effect the model is estimated for two separate sub-samples featuring exporters to the markets of the European Union (potentially more advanced trading partners) and markets of the Commonwealth of Independent States (countries of the same development levels). The results

[18] Service sectors have been excluded due to atypical results in those industry sub-groups.

of the estimation for selected industry sub-groups are shown in Table 6. Second part of Table 6 shows parameter estimates for the sample that features only EU exporters. In this case, we observe significant long-run ‘learning-by-exporting’ effect in *t+1* for labour-intensive (such as mining, food/beverages/tobacco) as well as capital-intensive (such as machinery, electrical and optical equipment and other manufacturing) industries. The results for the firms that seize exports to the EU are more mixed. Exporters of raw materials and goods of low levels of processing experience no significant productivity losses (and in case of agriculture even a productivity gain) after exiting export markets. At the same time negative productivity shock associated with export seizure is more pronounced for the exporters of capital intensive goods. Finally, in the case of service sectors we observe no significant productivity shock related to the the export market participation.

Finally, the last part of Table 6, features estimates for the sub-sample that concentrates on the exporters to the rest of the CIS countries. In this case we observe no statistically significant productivity effect for the first time entrants in the labour-intensive industries, while in capital-intensive industries and service sectors new exporters actually suffer productivity losses in the *t+1* period after entry. Labour-intensive firms experience no significant productivity losses after exiting CIS export markets. At the same time, capital-intensive and service sector exporters experience negative productivity shock in the period prior to exit (*t-1*) with no statistically significant productivity effect in period *t* and *t+1*.

The main contribution of the current study is an attempt to study the role of the export destination in the ‘learning-by-exporting’ effect. Our approach is similar to the one used by Harris and Li (2007). However, the use of the more extensive data set allows us make an extension to the empirical analysis distinguishing between different export destinations. Such analysis has not been implemented earlier. The only study that attemps to explore the role of export markets in export-productivity relationship is the one by Damijan *et. al.* (2005). However, due to the data limitations the study explored export-productivity nexus only on the aggregate level distinguishing between countries of the EU, OECD and Eastern European markets. Furthermore, using a dynamic system GMM approach as per Harris and Li (2007) allows us to account for self-selection and endogeneity that arise in the two-stage gross-accounting model (see Girma *et. al.*, 2004).

Overall, our results for the whole economy confirm previous findings of a positive productivity boost for the new exporters in periods *t* and *t+1*; negative productivity shock for the exiting firms (Bernard and Jensen, 2004; Girma et. al., 2004) and positive productivity gains while exporting for the firms that change their export status more than once (Harris and Li, 2007).

Table 4. Probit model estimation results. Marginal effects.

Industry classification	$lnLP_{t-1}$	$lnAge_{t-1}$	$lnEmp_{t-1}$	$lnEmp^2_{t-1}$	$Intange_{t-1}$	Pseudo R^2	No. Obs.
19 sub sectors	0.01637***	0.015***	0.078***	-0.098***	0.090***	0.167	676156
1. Agriculture/forestry/fishing	0.125***	0.121***	0.001***	-0.008***	0.067**	0.59	2870
2. Mining/quarrying of energy producing materials	0.089***	0.234***	0.004***	-0.009***	0.033	0.11	828
3. Mining/quarrying, except of energy producing materials	0.047***	0.048***	0.006***	-0.003***	0.121***	0.26	20641
4. Food/beverages/tobacco	0.044***	0 .026***	0..001***	-0.002***	0.079***	0.28	19365
5. Textile/clothing/leather/fur	0.034***	0.003	0.001***	-0.002***	0.148***	0.29	10793
6. Wood/wood products (+36)	0.099***	0.014	0.002***	-0.001***	0.141***	0.20	7068
7. Rubber/plastic	0.038***	0.032**	0.001***	-0.003***	0.166***	0.21	4462
8. Non-metallic minerals	0.039***	0.067***	0.005***	-0.002***	0.110***	0.22	7998
9. Basic/fabricated metals	0.053***	0.080***	0 .001***	-0.002***	0.210***	0.29	8688
10. Machinery and equipment	0.049***	0.131***	0.007***	-0.003***	0.186***	0.26	14267
11. Electrical and optical equipment	0 .031***	0.094***	0.006***	-0.002***	0.161***	0.27	13135
12. Transport equipment	0.067***	0131***	0.001***	-0.009***	0.294***	0.22	2865
13. Manufacturing n.e.c.	0.032***	0.028***	0.001***	-0.004***	0 .100***	0.25	7761
14. Wholesale trade	0.009***	0 .003***	0 .004***	-0.005***	0.019***	0.12	19154
15. Retail trade	0 .017***	0.031***	0.001***	-0.001***	0.054***	0.25	159966
16. Repair of motor vehicles	0.002***	-0.003***	0 .001***	-0.002	0.007***	0.15	83796
17. Transport/transport services/post	0.010***	0 .005***	0.005***	-0.003***	0.040***	0.12	36330
18. Real estate/renting/business activities	0 .084***	0. 185***	0.001***	-0.009***	0. 243***	0.28	4253

Note: Dependent variable: difference between treated and control TFP estimates. Robust standard errors in parentheses; ***- significant at 1% level; **- significant at 5% level; *- significant at 10% level. The model also includes *Industry* (on the aggregate level), *Region* and *Year* dummies

Table 5. Long-run 'learning-by-exporting' effect for Ukrainian Industries, 2000-2005

IV Model	A/B	CB	DA	DB/DC	**DK**	**DL**	**DN**	**G1**	**G2**	**I**
Exp_entry$_{t+1}$	.397	.152	.176	-.174	0.593***	0.281	0.331*	-0.423	-0.421	-0.049
Exp_entry$_{t}$	-.048	.186	.177	-.657	-0.047	1.351**	1.33**	-0.136	-2.82	-0.610
Exp_entry$_{t-1}$	.033	-.248***	-.238***	.085	-0.096***	0.054	-0.041	0.444**	-0.508***	-0.040
Exp_exit$_{t+1}$	.532*	.500*	.421	-.443	0.215	-0.427*	-0.258	0.010	-0.047	0.085
Exp_exit$_{t}$	2.32*	-.098	-.191	-1.20*	-0.093	0.389	-0.244	-1.97*	0.125	-0.813*
Exp_exit$_{t-1}$	-.126	-.102	-.129*	-.320**	0.100	-0.116	-0.305**	0.385***	0.123	-0.090
Exp_both$_{t+1}$	-.275	.762***	.660***	-.380	0.226	0.030	0.614***	0.616*	2.56***	-0.025
Exp_both$_{t}$	.082	3.28**	3.018*	.648	0.592	-0.407	1.97**	2.17	5.49	0.904
Exp_both$_{t-1}$	-.350	.612***	.579**	.172	0.004	-0.559**	0.056	-0.067	.768**	0.479**
No. of Obs	1162	5512	5022	1823	2944	1533	1123	1840	10083	6845
No of Groups	476	2404	2202	846	1100	570	458	802	4904	2488
Ar (1) z-stat	-2.43***	-5.96***	-5.68***	-3.89***	-6.01***	-5.52***	-4.05***	-4.72***	-6.78***	-10.77***
Ar (2) z-stat	1.04	-1.08	-1.05	-1.06	0.66	1.34	-1.28	0.77	-0.62	-0.72
Hansen test	27.94	77.63	79.79	45.59	28.21	90.68	69.59	82.27	63.33	42.51
Heckman	**A/B**	**CB**	**DA**	**DB/DC**	**DK**	**DL**	**DN**	**G1**	**G2**	**I**
Exp_entry$_{t+1}$	.445	.202	.246	-.167	0.521**	0.229	-0.233	-0.455	1.24**	-0.094
Exp_entry$_{t}$	.192	.418	.303	-.718	0.076	1.32**	1.33**	-0.191	4.10*	-0.842
Exp_entry$_{t-1}$	.051	-.235	-.227	.094	-0.068*	0.043	-0.038	0.632***	-0.503**	-0.084
Exp_exit$_{t+1}$	.586	.779*	.590	-.403	0.304	-0.450*	-0.303	0.080	-0.960	-0.030
Exp_exit$_{t}$	3.32	-.244	-.308	-1.35*	-0.232	0.384	-0.312	-1.58	-0.006	-0.805*
Exp_exit$_{t-1}$	-.022	-.126	-.133	-.342**	0.005	-0.067	-0.328*	0.250*	0.234*	-0.070
Exp_both$_{t+1}$	-.409	.758***	.662***	-.381	0.234	0.086	0.567***	0.667*	2.73***	0.024
Exp_both$_{t}$	.041	3.36**	2.93*	.957	0.786	-0.233	2.33**	1.60	7.29*	1.24
Exp_both$_{t-1}$	-.498	.559***	.558**	.169	0.025	-0.584**	0.087	-0.138	0.962***	0.500**
No. of Obs	1162	5512	5022	1823	2944	1533	1123	1840	10083	6845
No of Groups	476	2404	2202	846	1100	570	458	802	4904	2488
λ_1	-.051	-.083	-.067	-.021	-.195***	.075	-.0298	-.277*	.433***	.035
λ_0	.237	.015	.076	-.035	.061	.084	-.235*	.227	-.101	.171
Matching	**A/B**	**CB**	**DA**	**DB/DC**	**DK**	**DL**	**DN**	**G1**	**G2**	**I**
Exp_entry$_{t+1}$	-.822	.400	.335	-.434	0.516**	0.301	-0.244	-0.273	0.349	0.012
Exp_entry$_{t}$	9.78	-1.014	1.79	-4.20	0.363	1.15	0.926	5.53***	0.679**	-0.788
Exp_entry$_{t-1}$	-.207	-.105	-.271**	-.117	-0.054	0.185*	-0.074	0.424*	0.139	-0.097
Exp_exit$_{t+1}$	3.15	-.429	.921	.249	-0.187	-0.094	0.115	-0.146	-0.493	0.125
Exp_exit$_{t}$	26.7	2.801	.639	-3.61	0.007	1.24	0.449	-4.97***	-0.343	-0.958*
Exp_exit$_{t-1}$	.772	-.205	-.114	-.175	0.079	0.012	-0.086	0.357**	0.442**	-0.159*
Exp_both$_{t+1}$	-3.09	0.775*	-.467	.206	0.336	0.016	0.645***	0.272	3.42***	0.057
Exp_both$_{t}$	-45.5	-3.09	-5.61	12.8	1.17	-0.521	-1.31	4.99**	8.64**	0.750
Exp_both$_{t-1}$	-1.33	.433	.589	1.28	0.049	-1.02	-0.203	-0.038	-0.763	0.912***
No. of Obs	718	3266	2972	1031	1938	1000	707	1219	6541	4579
No of Groups	405	1883	1717	614	869	452	347	620	3627	1995

Note: For all three approaches presented in this table a 2-step system GMM estimator is used: instrument set included right hand side variables of the model; as well as logarithm of age and a dummy indicating possession of intangible assets. Standard errors in parentheses; ***- significant at 1% level; **- significant at 5% level; *- significant at 10% level.

Table 6. 'Learning-by-exporting' effect for Ukrainian Industries by destination, 2000-2005

General	**A/B**	**CB**	**DA**	**DB/DC**	**DK**	**DL**	**DN**	**G1**	**G2**	**I**
Exp_entry$_{t+1}$	0.397	0.152	0.176	-0.174	0.593***	0.281	0.331*	-0.423	-0.421	-0.049
Exp_entry$_{t}$	-0.048	0.186	0.177	-0.657	-0.047	1.35**	1.33**	-0.136	-2.82	-0.610
Exp_entry$_{t-1}$	0.033	-0.248***	-0.238***	0.085	-0.09***	0.054	-0.041	0.444**	-0.508***	-0.040
Exp_exit$_{t+1}$	0.532*	0.500*	0.421	-0.443	0.215	-0.427*	-0.258	0.010	-0.047	0.085
Exp_exit$_{t}$	2.32*	-0.098	-0.191	-1.20*	-0.093	0.389	-0.244	-1.97*	0.125	-0.813*
Exp_exit$_{t-1}$	-0.126	-0.102	-0.129*	-0.320**	0.100	-0.116	0.305**	0.385***	0.123	-0.090
Exp_both$_{t+1}$	-0.275	0.762***	0.660***	-0.380	0.226	0.030	0.614***	0.616*	2.56***	-0.025
Exp_both$_{t}$	0.082	3.28**	3.018*	0.648	0.592	-0.407	-1.97**	2.17	5.49	0.904
Exp_both$_{t-1}$	-0.350	0.612***	0.579**	0.172	0.004	-0.559**	0.056	-0.067	0.768**	0.479**
No. of Obs	1162	5512	5022	1823	2944	1533	1123	1840	10083	6845
No of Groups	476	2404	2202	846	1100	570	458	802	4904	2488
Ar (1) z-stat	-2.43***	-5.96***	-5.68***	-3.89***	-6.01***	-5.52***	-4.05***	-4.72***	-6.78***	-10.77***
Ar (2) z-stat	1.04	-1.08	-1.05	-1.06	0.66	1.34	-1.28	0.77	-0.62	-0.72
Hansen test	27.94	77.63	79.79	45.59	28.21	90.68	69.59	82.27	63.33	42.51
EU OECD	**A/B**	**CB**	**DA**	**DB/DC**	**DK**	**DL**	**DN**	**G1**	**G2**	**I**
Exp_entry$_{t+1}$	0.129	0.463***	0.504***	-0.045	0.329**	0.037*	0.180*	0.380	-0.431	0.285
Exp_entry$_{t}$	-2.150	-0.711	-0.716	0.373	-0.579	-0.220	0 .283	1.531	1.250	0.081
Exp_entry$_{t-1}$	0.016	-0.101**	-0.077*	-0.003	-0.059*	0.099	0.001	0 .422*	-0.073	-0.026
Exp_exit$_{t+1}$	0.679*	-0.254	-0.265	-0.723*	-0.169	-0.699***	-0.172	0.292	0.577	0.341
Exp_exit$_{t}$	0.374	-0.882	-1.023	-0.448	-1.012*	0.318	-0.513	-0.103	-1.422	-0.691
Exp_exit$_{t-1}$	-0.089	-0.066	-0.072	-0.151**	-0.083	-0.051	-0.105	0.089	0 .143	0.020
Exp_both$_{t+1}$	-0.173	-0.134	-0.015	0.155	0.267*	0 .347*	0.228	0 .031	2.002***	0.137
Exp_both$_{t}$	1.440	2.698	2.871*	-1.020	2.077***	0.905	-0.461	1.913	1.323	-0.542
Exp_both$_{t-1}$	0.584	0.231*	.244*	.198	0.142	-0.141	0.153	-1.252***	0 .132	0.429**
No. of Obs	1162	5512	5022	1823	2944	1533	1123	1840	10083	6845
No of Groups	476	2404	2202	846	1100	570	458	802	4904	2488
Ar (1) z-stat	1.03***	-5.54***	-5.60***	-5.69***	-6.33***	-4.96***	-3.88***	-5.44***	-7.64***	-9.79***
Ar (2) z-stat	1.03	-1.11	-1.01	-1.12	-1.18	1.07	-0.84	-0.19	0.30	0.47
Hansen test	25.97	57.00	62.97	59.22*	106.79*	85.48	64.81	53.81	134.88	67.22
CIS	**A/B**	**CB**	**DA**	**DB/DC**	**DK**	**DL**	**DN**	**G1**	**G2**	**I**
Exp_entry$_{t+1}$	0.108	0.150	0.142	-0.377	-0.484**	0 .183	-0.357*	-1.855***	-0.608	-0.262*
Exp_entry$_{t}$	-1.29	0.528	0.007	1.394	-0.385	1.636**	0.222	-3.049	-1.487	0 .446
Exp_entry$_{t-1}$	-0.210	-0.194**	-0.160	0.119	-0.107**	0.083	-0.174	0.503	-0.296	0.011
Exp_exit$_{t+1}$	0.778	0.481	0.158	0.336	0.285	-0.370**	0.227	-0.578	0.556	-.091
Exp_exit$_{t}$	-2.68	0.394	0.429	-1.594*	-0.536	-1.154	-1.002	0.555	0.032	0.319
Exp_exit$_{t-1}$	0.052	-0.034	-0.058	-0.428*	0.069	-0.203**	-0.346**	0.345*	0.133	-0.164**
Exp_both$_{t+1}$	-0.296	-0.483**	-0.399**	0 .187	0 .228	0.066	0 .484	1.770***	1.701***	0.231
Exp_both$_{t}$	2.075	-3.286*	-1.942	-1.063	1.521	-0.307	-1.259	4.182	1.277	-2.570**
Exp_both$_{t-1}$	0.053	0.423	0.304	-0.082	0.109	-0.163	0.426	-0.246	1.067***	0.494**
No. of Obs	1560	4874	4435	1398	2759	1397	953	1720	9149	6506
No of Groups	583	2211	2028	694	1066	530	407	768	4552	2413
Ar (1) z-stat	-1.79***	-4.52***	-4.79***	-3.43***	-5.80***	-5.23***	-3.34***	-4.73***	-6.68***	-10.36***
Ar (2) z-stat	1.01	-1.15	-1.13	-0.69	-0.49	0.53	-1.28	-0.86	-1.80	-1.11
Hansen test	20.13	62.67	71.41	34.95	58.23	87.05	68.37	52.55	48.17	56.62

Note: For all three approaches presented in this table a 2-step system GMM estimator is used: instrument set included right hand side variables of the model; as well as logarithm of age and a dummy indicating possession of intangible assets. Standard errors in parentheses; ***- significant at 1% level; **- significant at 5% level; *- significant at 10% level.

Table 7. Average 'learning-by-exporting' effect, 2000-2005

	Weighted average all industries	Weighted Average excl. Retail and Wholesale Trade and Repair of Motor Vehicles
General		
Exp_entry$_t$	0.064	0.112
Exp_entry$_t$	0.103	0.180
Exp_entry$_{t-1}$	-0.232	0.069
Exp_exit$_{t+1}$	0.066	0.066
Exp_exit$_t$	-0.199	-0.249
Exp_exit$_{t-1}$	-0.022	-0.035
Exp_both$_{t+1}$	0.861	0.135
Exp_both$_t$	-0.498	-0.087
Exp_both$_{t-1}$	0.438	0.231
EU OECD		
Exp_entry$_t$	0.144	0.251
Exp_entry$_t$	0.029	0.051
Exp_entry$_{t-1}$	-0.027	0.034
Exp_exit$_{t+1}$	-0.012	-0.022
Exp_exit$_t$	-0.176	-0.220
Exp_exit$_{t-1}$	-0.032	-0.025
Exp_both$_{t+1}$	0.760	0.022
Exp_both$_t$	0.291	0.508
Exp_both$_{t-1}$	0.031	0.117
CIS CEEU		
Exp_entry$_t$	-0.169	-0.201
Exp_entry$_t$	0.019	0.033
Exp_entry$_{t-1}$	-0.018	-0.009
Exp_exit$_{t+1}$	-0.014	-0.025
Exp_exit$_t$	-0.095	-0.166
Exp_exit$_{t-1}$	-0.025	-0.060
Exp_both$_{t+1}$	0.686	-0.016
Exp_both$_t$	-0.493	-0.062
Exp_both$_{t-1}$	0.468	0.067

Note: Average of all estimates in table 5, significant at least at 15% level weighted by industry shares of the total real gross output in all industries.

Summary

This paper presents an attempt to estimate the ways in which exporting might influence a firm's performance and productivity at the micro-level on the basis of the dataset covering main Ukrainian manufacturing and service sectors during the period 2000-2005. In doing so, current study measures the productivity effect that occurs before entering export markets (self-selection effect) as well as the effect that occurs in the post-entry period (learning-by-exporting effect).

The estimation of self-selection hypothesis is done on the basis of a probit model. The results of the estimation studying the firms which started exporting at any time during the reported period for the thirteen manufacturing and five trade and service sectors go in line with previous findings in the literature on self-selectivity. The results show mainly that firms with higher TFP in the period *t-1* are much more likely to enter export markets in the period *t.* Also age, size and intangible assets of the firm, have significant positive influence on the probability of exporting.

The next part of the analysis studies the productivity effects that occur after the entry into overseas markets (learning-by-exporting effect). The analysis is implemented with the help of the dynamic system GMM approach to account for the issues of endogeneity and sample selection. Heckman control function procedure and propensity score matching are further used as robustness checks. The quality of the matching procedure is verified using '*ptest*' (Leuven and Sianesi, 2003). The results of the analysis confirm the presence of the learning-by-exporting effect in the majority of industries under study. The results for the whole economy, given in Table 7, confirm positive productivity boost for the new exporters in periods *t* and *t+1*; negative productivity shock for the exiting firms (Bernard and Jensen, 2004; Girma et. al., 2004) and positive productivity gains while exporting for the firms that change their export status more than once (Harris and Li, 2007). The results however are not universal across the industries. Labour-intensive industries and service sectors show no statistically significant productivity gains in the post-entry period. Furthermore, in some cases there is positive productivity boost associated with export seizure. Capital-intensive industries on the other hand experience a positive/negative productivity shock after entering/exiting export markets. Finally, majority of the industries, experience a negative productivity shock in a pre-entry period, which might be related to the sunk cost of exporting associated with product rebranding, establishing logistics and distribution channels and other activities of similar sort.

Furthermore, when exporting is targeted at the advanced export markets (EU countries), capital-intensive industries experience more pronounced productivity shocks associated with exporting; while labour intensive industry sub-groups show weaker long-run 'learning-by-exporting' effect. Service sectors, however, show no significant 'learning-by-exporting' effect of any kind. Finally, when exporting to the CIS countries, first time entrants in the labour-intensive industries experience no statistically significant productivity gains, while in capital-intensive industries and service sectors new exporters actually suffer productivity losses in a year following entry. Moreover, labour-intensive firms experience no significant productivity losses after exiting CIS export markets. At the same time, capital-intensive and service sector exporters experience negative productivity shock in the period prior to exit (*t-1*) with no statistically significant productivity effect in the year of exit and subsequent year.

In order to reveal common trends behind the 'learning-by-exporting' results, it might be useful to compare the results of the current study to some of the previous findings. The paper by Harris and Li (2007) is one of the most recent examples and also one of the best to use for comparison. The authors provide estimates for the 16 separate industries in the UK for the period 1996-2004. Despite the fact that the format of the aggregation across different output sectors is slightly different from the one used in our analysis, the structure of the analysis still allows us to compare these two sets of results.

Table 8. Presence of learning-by-exporting effect in separate industries

NACE	Industry	Harris and Li	Current Study (Overall Effect)
(A/B)	Agriculture/forestry/fishing	-	-
(CA)	Mining/quarrying of energy producing materials	N/A	+
(CB)	Mining/quarrying, except of energy producing materials	N/A	-
(DA)	Food/beverages/tobacco	+	-
(DB/DC)	Textile/clothing/leather/fur	+	-
(DD)	Wood/wood products (+36)	+	+
(DE)	Paper/printing/publishing	+	N/A
(DF/DG)	Coke/nuclear/chemical	+	N/A
(DH)	Rubber/plastic	+	+
(DI)	Non-metallic minerals	-	-
(DJ)	Basic/fabricated metals	-	-
(DK)	Machinery and equipment	+	+
(DL)	Electrical and optical equipment	+	+
(DM)	Transport equipment	+	+
(DN)	Manufacturing n.e.c.	+	+
(G1)	Wholesale trade	-	-
(G2)	Retail trade	-	-
(G3)	Repair of motor vehicles	-	-
(I)	Transport/transport services/post	-/-/+	-
(K)	Real estate/renting/business activities	+	+
	Total	**+**	**+**

Note: See Harris and Li (2007) for the complete list of their results. "+" – significant at the 10% or less learning-by-exporting effect; "-" - insignificant learning-by-exporting effect.

The comparison presented in Table 8 shows that capital-intensive sectors, such as machinery and equipment; electrical and optical equipment; transport equipment; manufacturing n.e.c. enjoy productivity gains from exporting both in the UK and Ukraine. Labour-intensive sectors (agriculture/forestry/fishing; non-metallic minerals, basic fabricated minerals) on the other hand show no significant long-run productivity gains from exporting in both studies. On average, for the whole economy, the results of both studies suggest substantial positive long-run productivity effect for the firms that enter export markets; negative productivity effect for the firms that exit from exporting and positive productivity gains during exporting for the firms that change their export status more than once.

Our approach has been widely applied in the literature on the exports-productivity linkages. Main contribution of the current study is an extensive data set that allows us to explore the export-productivity nexus at the industry level as well as for different export destinations. Furthermore, the study employs IV approach in a dynamic system GMM setting to account for endogeneity and selection bias. Heckman two-stage approach and propensity score matching procedure are further used as robustness checks. Main results of the analysis confirm that differences in productivity between exporting and non-exporting firms can be partially attributed to higher productivity levels of exporters prior to entering export markets (which allows them to overcome entry barriers more easily). Furthermore, the results of the estimation provide us with the evidence in favour of the learning-by-exporting hypothesis, showing long-run productivity gains for the first time entrants into exporting and productivity losses for the firms that exit. The effect is more pronounced in capital intensive sectors, especially when exporting is targeted at more advanced markets. At the same time exporting to the countries of similar or lower development levels can have a deteriorating effect on a TFP of a capital-intensive firm.

Recent literature suggests several reasons for the weak support of the 'learning-by-exporting' effect in labour-intensive industries. First of all, exporters of labour-intensive products and raw materials rely mainly on the low-cost advantage rather than new technologies developed through the R&D investment. Furthermore, as noted by Kogut and Zander (1996) firm's specific assets such as experience; knowledge-base; human capital assets and managerial practices are important determinants of its ability to overcome entry barriers to foreign markets. At the same time this allows us to conclude that these assets play an important role in the ability of the firm to absorb further benefits coming from exporting and government policy should consider how it might best increase overseas market entry through ensuring that potential exporters have the assets required.

In terms of policy implications, our findings suggest that government policies aimed at increasing R&D investment and stimulating development of the technology-intensive sectors would increase the ability of domestic firms to overcome foreign market barriers as well as assimilate further benefits arising from exporting, which can further enhance international competitiveness of Ukrainian firms.

References

1. Alvarez, R. (2001) external Sources of Technological Innovation in Chilean Manufacturing Industry. *Estudios de Economia*, 28(1), 53-68.
2. Arellano, M. and Bond, S. R. (1998) Dynamic Panel Data Estimation Using DPD98 for GAUSS: A Guide for Users.
3. Aw, B. Y., and A. Hwang (1995) Productivity and the export market: A firm level analysis. *Journal of Development Economics*, 47, pp. 313-332.
4. Aw, B. Y., S. Chung, and M. J. Roberts (2000) Productivity and turnover in the export market: micro evidence from the Republic of Korea and Taiwan (China). World Bank Economic Review 14, 65-90.
5. Baldwin, J. R. and Gu, W. (2004) Trade liberalization: Export market participation, Productivity Growth and Innovation. *Oxford Review of Economic Policy*, 20(3), 372-392.

6. Baldwin, J. R. and Gu, W. (2003) Export-Market Participation and Productivity Performance in Canadian Manufacturing. *Canadian Journal of Economics*, 36(3), 634-657.
7. Barney, J. (1991) Firm Resources and Sustained Competitive Advantage. *Journal of Management*, 17(1), 99-120.
8. Bernard, A. B., Eaton, J., Jensen, J. B., and Kortum, S. (2003) Plants and Productivity in International Trade. *American Economic Review*, 93, 1268-1290.
9. Bernard, A. B., and J. B. Jensen (1999) Exceptional exporter performance: cause, effect or both? *Journal of International Economics*, 47(1), 1-25.
10. Bernard, A. B. and Wagner, J. (1997) Exports and Success in German Manufacturing. *Review of World Economics*, 133(1), 134-157.
11. Bleaney, M. and Wakelin, K. (2002) Efficiency, Innovation and Exports. *Oxford Bulletin of Economics and Statistics*, 64(1), 3-15.
12. Brown, J. David, John S. Earle (2008). Microcredit, Employment, Sales and Survival: An Empirical Evaluation Using a Panel Matching Estimator. Heriot-Watt University and CEU Labour Project.
13. Carlton, D. W. (2005) Barriers to Entry. NBER Wroking Paper 11645.
14. Castellani, D. (2002) Export Behavior and Productivity Growth: Evidence from Italian Manufacturing Firms. *Review of World Economics*, 138(4), 605-628.
15. Clerides, S. K., S. Lach, and J. R. Tybout (1998) Is learning-by-exporting important? Micro-dynamic evidence for Colombia, Mexico, and Morocco. *Quarterly journal of Economics* 113, 903-48.
16. Cohen, W. M. and Levinthal, D. A. (1989) Innovation and Learning: the Two Faces of R&D. *The Economic Journal*, 99, 569-596.
17. Damijan, J., Polanec, S., and Prasnikar, J. (2005) Does exporting increase Productivity? Firm Level Evidence from Slovenia. Paper presented at conference on ‘Globalization and Firm Level Adjustment’, University of Nottingham.
18. Delgado, M. A., J. C. Farinas, and S. Ruano (2002) Firm productivity and export market: a non-parametric approach.
19. Farinas, J. C. and Martin-Marcos, A. (2003) Exporting and Economic Performance: Firm-Level Evidence for Spanish Manufacturing.
20. Girma, S., Greenaway, D., and Kneller, R. (2004) Does Exporting Increase Productivity? A Microeconomic Analysis of Matched Firms. *Review of International Economics*, 12(5), 855-866.
21. Girma, S., Kneller, R., and Pisu, M. (2005) Exports vs FDI: An Empirical Test. *Review of World Economics*, 141(2), 193-218.
22. Greaway, D. and Yu, Z. (2004) Firm Level Interactions between Exporting and Productivity: Industry-Specific Evidence. *Review of World Economics*, 140, 376-392.

23. Greenaway, D., Gullstrand, J., and Kneller, R. (2005) Exporting May Not Always Boost Firm Productivity. *Review of World Economics*, 141(4), 561-582.
24. Greenaway, D. and Kneller, R. (2004) Exporting Productivity in the United Kingdom. *Oxford Review of Economic Policy*, 20, 358-371.
25. Greenaway, D. and Kneller, R. (2005) Exporting and Productivity: Theory, Evidence and Future Research. *The Singapore Economic Review*, 50, 303-312.
26. Hallward-Driemier, M., Iarossi, G., and Sokoloff, K. L. (2002) Exports and Manufacturing Productivity in East Asia: A Comparative Analysis with Firm-Level Data. Available at http://search.epnet.com/login.aspx?direct=true&db=ecn&an=0715248
27. Harris, R. I. D. And Li, Q. (2007) Learning by Exporting? Firm Level evidence for UK Manufacturing and Service Sectors. Working paper, Dept. Of Economics, University of Glasgow
28. Javorcik, Beata Smarzynska (2004) Does foreign direct investment increase productivity of domestic firms? In search of spillovers through backward linkages. *American Economic Review* 94, 605-627.
29. Kraay, A. (1999) Exports and Economic Performance: Evidence from a Panel of Chinese Enterprises. *Revue d'Economie Du Developpement*, 0(1-2), 183-207.
30. Konings, Jozef and Vandenbussche, Hylke (2004) Antidumping protection and productivity growth of domestic firms. CEPR Discussion Paper 4620.
31. Lopez, R. A. (2004) Self-Selection into Export Markets: A Conscious Decision? *Indiana University Paper.* https://editorialexpress.com/cgi-bin/conference/download.cgi?db_name=mwetit2005&paper_id=22
32. Melitz, M. J. (2003) The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica*, 71(6), 1695-1725.
33. Shevtsova, Y. (2010) International Trade and Productivity: Empirical Evidence from Ukraine. *DIW Working Papers*
34. Teece, D. J., Pisano, G., and Shuen, A. (1997) Dynamic Capabilities and Strategic Management. *Strategic Management Journal*, 18(7), 509-533.
35. Wagner, J. (2005) Exports and Productivity: A survey of the Evidence from Firm Level Data. *University of Lueneburg, Institute of Economics, mimeo*, March.

Appendix 1. Ukrainian export-import structure, selected industries

Category	Export 2002	Import 2002	Export 2005	Import 2005	Export 2008	Import 2008
Food & beverages	2388933.75	1113761.33	4307004.9	2684081.89	10830635.3	6456568.1
Mineral products	2244887.94	7047279.28	4707983.04	11567831.37	7046089.7	25441471
Coke/ Chemical	1397046.43	1375005.12	2990247.4	3097918.28	5045387.7	6959125.1
Rubber/ Plastics	262735.1	736233.91	575238.83	1938136.24	997666.2	4476816.6
Leather/fur	159063.06	58560.96	211085.31	111179.36	359518.9	232455.4
Wood products	289678.9	84998.2	533924.35	199883.28	801168.1	545722.5
Wood/ Timber	278633.17	682004.26	454335.89	1004118.63	874402.5	1835249.1
Textile/ Cloth	654650.68	673007.43	914034.36	1406190.76	984587	2099247.4
Shoes	75961.07	53646.21	107759.95	279287.31	178099.1	531113
Textile/ Clothing	730611.75	726653.64	1021794.31	1685478.07	1162686.1	2630360.4
Stone/cast/ ceramic/glass goods	147298.89	202359.21	218679.66	516192.6	454820.3	1276483.6
Fabricated metals	7125620.2	810919.76	14047248.78	2468818.31	27633085.3	6390049.9
Machinery/ electrical machinery/ Equipment	1758609.21	2502043.63	2841800.99	6342271.65	6341164.6	13378597.5
Motor vehicles and transport equipment	689335.43	1021519.26	1655874.59	3219711.33	4324092.3	12091355.8
Medical/ precision equipment	182892.48	267213.09	141934.28	507425.38	242906.4	1222606.7
Other manufacturing	96626.67	135920.04	218408.4	323120.61	438909.6	1011012.8
Art works	79.01	500.63	186.93	732.27	723.4	4105.9
Other	198566.63	118697.51	244770.52	36554.18	242914	35444.9

Note: Selected years, 2002, 2005, 2008; expressed in '000 USD