International Trade and Productivity: The Role of Industry and Export Destination

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Abstract

The study explores the productivity effect associated with all types of firm's export decisions across destinations. Using micro data on Ukrainian manufacturing firms operating during 2000-2005, I show that high-tech firms experience stronger productivity shocks associated with changes in their export status. Low-tech firms, instead, experience productivity improvements only when entering advanced export markets and are, on average, significantly less sensitive to changes in their export status. The results also show that firms' characteristics, including productivity, not only improve the firm's ability to self-select into exporting, but also increase its ability to penetrate a larger number of export markets.

JEL codes: D24; F14; L25

Keywords: exports; TFP; destination specific learning-by-exporting effect, export diversification, system GMM

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1 Introduction

The empirical studies on the exporting-productivity links, following pioneering work by Aw *et al.* (1998) and Bernard and Jensen (1999), have explored a number of mechanisms that make exporters more productive than their non-exporting counterparts (see Greenaway and Kneller (2007), Wagner (2007a) for surveys of literature). These mechanisms can be summarised in two main effects.

The first one is a *self-selection* effect which presumes that, on average, potential exporters have higher productivity prior to entry when 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.[1] The second channel that links exports to firm productivity, so called *learning-by-exporting* effect, suggests that firms that start exporting benefit from further advances in their productivity after the entry took place. While theoretical side of the learning-by-exporting hypothesis has been well explained (Isgut and Fernandes, 2007; Eaton *et. al.*, 2011; Crino and Epifani, 2012), the available empirical evidence is more mixed.[2]

This paper contributes to the literature by exploring destination-related aspect of the self-selection and the learning-by-exporting effects using a comprehensive firm-level dataset of Ukrainian manufacturing firms for the period 2000-2005. This issue has emerged only recently and, while theoretical studies (Lawless, 2009) suggest that the number of export destinations (regions/countries) is positively related to firm's productivity, the amount of empirical evidence is still relatively scarce. The majority of studies on destination related aspects of export-productivity nexus use the data on advanced, high income countries. Wilhelmson and Kozlov (2007) – based on the Russian manufacturing micro-data - is the only study that documents the learning-by-exporting effect for a Commonwealth of Independent States (henceforth, CIS) country. Ukraine in itself is an interesting case to explore. It is a former USSR (and further CIS) country transformed from socially planned to market economy in a short period of time. Currently, Ukraine is classified as emerging market in the IMF World Economic Outlook with its GDP per capita reaching only around 7% of the EU average in the last decade. At the same time world integration has led to an increase in Ukraine's international trade of about over 100% between 2000 and 2005. The period of study coincides with CIS economic recovery from the 1998 Russian financial crisis and exhibits high degree of dynamism in export markets – the number of Ukrainian firms entering export markets between 2000 and 2005 has increased more than twice.

More in detail, the first part of the paper studies the impact of firm characteristic on the number of potential export destinations. While the link between firm characteristics and export participation has been well documented, the choice of the number of export markets per se has been explored only in a

[1] Aw and Hwang (1995); Bernard and Jensen (1995, 1999, 2004)
[2] Silva et al (2010a) provide an extensive survey of the learning-by-exporting literature.

limited number of empirical studies (Muuls and Pisu, 2009; Cestellani *et al.*, 2010; Andersson *et al.*, 2008 and Eliasson *et al.,* 2009). The available empirical findings, based mostly on aggregate descriptive statistics and linear regression analysis, suggest that only a small share of firms serve a large number of markets, while the majority of exporters concentrate on a small number of export destinations. At the same time, the link between firms' heterogeneity and the choice of the number of export destinations can be better addressed using count data models that account for the discrete non-negative nature of the data (Ferrante and Novelli, 2012). This paper fills in the gap and provides new empirical evidence on the impact of firm characteristics on the choice of the number of export markets using count data regression models.

The second part of the paper provides new evidence on the impact of exporting on firm performance (learning-by-exporting effect) using the full set of destination-specific firm export decisions. To account for selection bias, the estimation of the post-entry productivity improvements is implemented using instrumental variables (hereafter IV) and the system GMM approach (Blundell and Bond, 2000). The empirical model distinguishes between firms that start exporting, cease exporting or change their export status more than once. This full set of firm export decisions is estimated for different export destinations.[3]

Finally, many empirical studies highlighted the role of industry heterogeneity in the learning-by-exporting effect, suggesting that knowledge-absorptive capacities (i.e. firm abilities to internalize new knowledge) can differ between industries (De Loecker, 2007; Harris and Li, 2012). At the same time these sectoral differences have not been formally addressed. In an attempt to take a more systematic approach to industry heterogeneity in the learning-by-exporting effect the estimation in this study is performed separately for the sectors with low and high technology intensity (hereafter: low-tech and high-tech). The technology intensity of the sector is identified using the OECD industry technology intensity classification.[4]

The results suggest that productivity and intangible assets increase the ability of the firms in high-tech sectors to penetrate a larger number of export markets, while for the firms in the low-tech sectors both productivity and intangible assets have a less pronounced effect on the ability of the firm to target wider range of export destinations. At the same time, foreign owned firms in the low-tech sectors tend to export to the home countries of their global owners, highlighting the role of the global value chain (hereafter, GVC) effect in shaping export activity of the low-tech firms.

Regarding the learning-by-exporting effect, the results show that the effect depends on the type of industry and target export market. For example, in high-tech sectors productivity benefits arise only

[3] The analysis distinguishes between the following destinations: tax heavens, emerging markets, CIS and advanced markets. Destination regions were designed using IMF World Economic Outlook country classification: https://www.imf.org/external/pubs/ft/weo/2015/02/weodata/groups.htm

[4] OECD sector technology intensity classification: http://www.oecd.org/sti/ind/48350231.pdf

when firms start exporting to the advanced, highly industrialized markets; while exporting to the countries of the same or lower development levels does not bring any significant productivity benefit. At the same time, high-tech firms' productivity losses are associated with the termination of the export activity irrespective of the type of export destination. Overall, firms in the high-tech industries experience more pronounced productivity shocks associated with the full spectrum of export participation decisions (entry, exit, switching).

On the other hand, the productivity evolution of the firms in the low-tech sectors is much less sensitive to the changes in the firm export status. In fact, in the low-tech sectors productivity gains arise only when exports are aimed at the advanced, high-income markets. At the same time, low-tech companies experience no significant productivity losses when exiting international markets irrespective of the type of export destination.

These results shed further light on the learning-by-exporting effect. While most of the existing studies estimate the impact of exporting on the firm learning process using aggregate manufacturing data, the current study distinguishes between the high-tech and low-tech firms, showing that productivity effects associated with changes in export status may differ significantly depending on the technology intensity of the industry where the firm operates. Such differences might result from different absorptive capacities and different *ex ante* incentives for exporting in the high-tech and low-tech firms. While high-tech firms enter global markets as a result and with a purpose of further technological development, low-tech firms mostly commence exporting while taking part in a GVC process.

The rest of the paper is structured as follows. The next section provides a brief review of the studies on export destination and productivity. Section 3 presents the dataset and provides a preliminary analysis of the productivity differences between exporting and non-exporting firms. Sections 4 and 5 provide a description of the estimation methodologies and present the results of the estimation of the self-selection and the learning-by-exporting effects by destination. A summary and some concluding remarks are presented in section 6.

2 Literature Review and Motivation

Many empirical studies have found superior performance characteristics in exporting firms.[5] Papers by Clerides *et al.* (1998), Melitz (2003) and Bernard *et al.* (2003) provided formal theoretical frameworks to show that more productive firms self-select into export markets, giving rise to the *self-selection hypothesis*. The reasons for better performance of exporting firms can be clearly identified. Entrance and successful operation in export markets depend upon the ability of the firm to bear sunk-entry export costs, including the costs of marketing, distribution, establishing foreign networks, adapting

[5] Wagner (2007a) and Greenaway and Kneller (2007) provide comprehensive reviews of the literature on exports-productivity links.

domestic products to the tastes of foreign customers and on the firm's ability to sustain competition with foreign rivals. This implies that only firms whose productivity is above a certain threshold will manage to enter and successfully operate in international markets.[6]

Furthermore, the nature of sunk-entry costs suggests that at least some of them tend to recur for each new export market. Blanes-Cristobal *et al.* (2008) confirm that entry costs indeed tend to differ among export destinations, implying that higher productivity is required to serve larger number of export markets (Lawless, 2009). A number of successive empirical studies have found a positive correlation between productivity and the number of export markets served (Muuls and Pisu, 2009; Wagner, 2007b; Lawless, 2009; Castellani *et al.*, 2010). At the same time the *ex-ante* impact of firm productivity and other firms' characteristics on its ability to penetrate wider range of export markets has been little explored.

An alternative explanation of the productivity differences between exporting and non-exporting firms, the so called *learning-by-exporting* effect, suggests the existence of post-entry productivity gains for the firms that engage in international trade. However, the empirical analysis of the learning-by-exporting effect has been complicated by the selection bias associated with export participation decisions. A number of empirical studies tried to disentangle the self-selection and the learning-by-exporting effects and estimate post-entry productivity improvements controlling for the selection of export decisions. So far, however, the evidence has been mixed. A number of empirical studies found evidence in favour of the learning-by-exporting effect using the data from developing countries with increasing export shares, changes in the export structure and low technological frontiers.[7] At the same time the evidence on learning-by-exporting in advanced economies with stable export shares, experienced exporters and strong domestic market competition has been weak.[8][9] A cross-country study by the International Study Group on Exports and Productivity (2009) provides comparable empirical evidence on 14 European countries, with a strong support of self-selection and almost no evidence of learning-by-exporting effects.

The nature of the learning-by-exporting effect also suggests that productivity benefits should differ between destination countries (Crino and Epifani, 2012). Indeed, productivity gains are expected to be higher when the target export markets are highly developed providing access to the latest technologies, product designs, technical and managerial expertise, which, together with economies of

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[6] A recent paper by Ricci and Trionfetti (2012) points out that foreign and domestic network participation can significantly increase firm's propensity to export.

[7] Delgado *et al.*, 2002; Lileeva and Trefler, 2007; Hallward-Driemeier *et al.,* 2002; Blalock and Gertler, 2004; Isgut and Fernandes, 2007.

[8] Baldwin and Gu (2004), Castellani *et. al.* (2010) provide evidence of post-entry productivity improvements, at the same time Greenaway *et al.* (2005) and Wagner (2002) find no evidence of learning-by-exporting effect for German manufacturing firms.

[9] For a survey of recent literature on learning-by-exporting please see Silva *et al*. (2010a) and a meta-study by Martins and Yang (2009).

scale, contribute to the overall improvement of the manufacturing process (Wagner, 2012). Furthermore, higher quality standards and higher intensity of competition in the advanced foreign markets can boost the productivity of the new exporters by stimulating them to innovate, improve their technologies and change their personnel composition towards highly-skilled workers (Verhoogen, 2007).

However, due to the data limitations, the extant empirical studies have added the aspect of export destination to their analysis of learning-by-exporting effect only recently.[10] Most of these studies use micro-level data on highly industrialized countries and provide inconclusive evidence in favour of learning-by-exporting hypothesis by export destination. Pisu (2008) finds no evidence of destination related learning-by-exporting effects, concluding that productivity advantages in Belgian manufacturing exporters are driven solely by self-selection. Silva *et al.* (2010b) find that only exporters to more developed markets that reached a high level of export intensity enjoy post-entry productivity benefits. Wilhelmsson and Kozlov (2007) - the only study that explores the learning-by-exporting effect using micro-level data for a CIS country - find no conclusive evidence of learning-by-exporting effect for Russian manufacturing firms. Finally, several empirical studies based on Slovenian data provide mixed evidence of the learning-by-exporting. Damijan *et al.* (2004) show that post-entry productivity improvements occur only in cases when exporting is targeted at advanced foreign markets, while De Loecker (2007) - using a cross-section snapshot of firm export destinations - shows that all exporters enjoy additional post-entry productivity gains, however, productivity premia are significantly higher in case of serving advanced markets. Finally, Kostevc (2009) using the same dataset on Slovenian manufacturing firms finds inconclusive evidence of the post-entry learning process for the new exporters irrespective of the target export market.

Overall microeconometric studies on the destination-specific export productivity links suggest that the self-selection of firms tends to be market specific, with more productive firms penetrating more demanding markets and that the productivity and other firm performance characteristics are positively correlated with the number of export markets served. At the same time the evidence on the role of export destination on the post entry learning effects is inconclusive (Wagner, 2012). Furthermore, despite acknowledging industry heterogeneity, most of the studies on learning-by-exporting, address the issue using aggregate manufacturing data, overlooking the fact that firms' absorptive capacity (i.e. the ability to internalize external knowledge) may differ significantly between industries. The current paper attempts to address this aspect, by estimating the learning-by-exporting effect distinguishing among export destinations and sectoral technology intensity.

[10] Wagner (2012) provides a comprehensive summary of empirical literature on export destination and productivity.

3 Data and Preliminary Analysis

3.1 Data and Descriptive Statistics

This paper uses the data submitted to the Ukrainian Office of National Statistics (Derzhkomstat) that groups consolidated annual accounts data on the census of Ukrainian manufacturing and service firms operating in Ukraine between 2000 and 2005.[11] All firms are uniquely defined by their VAT (EDRPOU) number and divided into sectors according to the Ukrainian Office of National Statistics nomenclature, which is comparable to the NACE Rev.1 classification. The data contain information on firm-specific characteristics, such as employment (measured as the annual average number of registered employees), output, sales, tangible and intangible assets, material costs and other types of intermediate expenditures (including R&D and innovation expenditure), and gross capital investment. The dataset is merged with the Ukrainian Customs office data that contains information on the monetary value of firm-level exports by country and year. All variables were deflated using price deflators available from the Ukrainian Office of National Statistics.[12]

I limit the study to cover the firms in the manufacturing sectors (NACE Rev. 1 15-36[13]) with at least one employee. The final dataset used for statistical analysis comprises an unbalanced panel with an average of 35,536 firms per year and 194,431 observations covering the period 2000-2005, with information showing entry and exit from export markets. Table 1 shows that the average annual percentage of exporting firms in the sample is 14.7%.

[Table 1 about here]

Table 2 contains summary statistics for the basic variables - output, capital, employment and material costs - for selected years. The statistics show increasing output and material expenditure and declining average size and capital, caused primarily by productivity growth and increasing number of small and medium market entrants during 2000-2005.

[Table 2 about here]

The employment figures in Table 2 might cause a concern that large firms might be over-represented in the sample. However, according to the Enterprise Survey data collected by the World Bank Group[14] 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

[11] The data is restricted and not available for public use. The unit of observation is referred to as "firm" in the text.
[12] Ukrainian State Statistic Committee website: http://www.ukrstat.gov.ua/
[13] I exclude Recycling sector (NACE rev. 1: #37) from the analysis.
[14] http://www.enterprisesurveys.org/.

firm – only 37.3 workers. Moreover, firms in manufacturing are more than twice as large as those in retail and other services.

For the purpose of the empirical analysis, I distinguish between two groups of sectors using the Technology Intensity Classification provided by the Organization of Economic Cooperation and Development (hereafter OECD) as a guide.[15] By using this method of aggregation I identify the differences in the impact of a firm specific characteristics on its export choice, for the high-tech and low-tech firms. Table 3 summarises the industries included in each category and provides summary export participation statistics by group.

[Table 3 about here]

3.2 Preliminary Analysis

This section performs a preliminary analysis to compare the characteristics of exporting and non-exporting firms in Ukraine.

First, following Bernard Jensen (1999), De Loecker (2007), Andersson *et al.* (2008) *inter alia*, I calculate the export premia for Ukrainian firms by estimating the OLS regression of the following form:

$$x_{ikt} = \alpha + \beta * EXP_{ikt} + \gamma * e_{ikt} + \sum_j \delta_j * YEAR_j + \sum_k \lambda_k IND_k + \varepsilon_{ikt} \qquad (1)$$

where $\boldsymbol{x_{ikt}}$ refers to the characteristics of firm *i* at period *t* operating in industry group *k, EXP* is a dummy indicating firm's export status, $\boldsymbol{e_{ikt}}$ is the logarithm of the firm employment, *YEAR* and *IND* refer to the time and industry controls. The coefficient β shows whether the characteristic of an exporting firm is different from the one of its non-exporting counterpart, i.e. the firm export premium. Table 4 shows the estimation results that confirm significant differences in characteristics between exporters and non-exporters, in both the high and the low-tech sectors.[16]

[Table 4 about here]

In line with previous studies (Bernard and Jensen, 1995; Bernard and Wagner, 1997; Isgut, 2001; De Loecker, 2007) the results confirm that exporters in both low and high-tech sectors are larger in size, sell more, pay higher wages, and have higher levels of investment and capital intensity and a significantly higher labour productivity.

Despite being located in the geographic center of Europe Ukraine is not a member of the European Union (hereafter, EU) and the long-awaited Deep and Comprehensive Free Trade Area Agreement

[15] Technology Intensity OECD Classification can be found here: http://www.oecd.org/sti/ind/48350231.pdf. Eurostat adopted the definition transforming it to NACE Rev.1 and later to NACE Rev. 2.
[16] The estimation combines the first two groups (Low Technology Industries and Medium-Low Technology Industries) and the second two groups (Medium-High Technology Industries and High Technology Industries). The same level of aggregation is used in the remainder of the paper.

between the EU and Ukraine has not been fully implemented as of November 2015. Furthermore, Ukraine has become a member of the WTO only in May 2008. Hence, it is likely that during 2000-2005 Ukrainian export firms were facing high levels of sunk entry costs, especially when selling to more advanced markets. Indeed, the results in Table 4 show that export premium on labour productivity for Ukrainian firms was at least five times higher than the productivity premium of Swedish exporters (Andersson *et al.*, 2008, report 14 percent productivity premium for Sweden) and twice as high as the productivity premium of Slovenain exporters (De Loecker, 2007).

Next, I use total factor productivity (TFP) - a more reliable productivity measure – to test the rank ordering of the distribution of exporting versus non-exporting firms (Girma *et al.*, 2004; Wagner, 2007b).[17] Table 5 shows that in high-tech sectors the TFP distribution of exporters dominates that of non-exporters. At the same time in the low-tech sectors there is an evidence of some cross-over between the two sub-groups.

[Table 5 about here]

Overall, our preliminary analysis reveals a significant export premium for Ukrainian exporters. The next sections will explore the association between the choice of export destination and the productivity of Ukrainian manufacturing firms.

4 Self-Selection: The Role of Industry and Export Destination

4.1 Econometric Modelling

The main purpose of this section is to estimate the causal effect of firm-specific characteristics on its choice of the number of export destinations by addressing the problem of self-selection along the country-extensive margin.

The abundant empirical evidence of firms' self-selection into exporting points out that inter-firm variations in export participation crucially depend on the underlying firms' characteristics, including their productivity, as well as sunk costs of entry into international markets (Greenaway and Kneller, 2007). Theoretical trade models with asymmetric countries and sunk costs advocate that self-selection is market specific, i.e. firms with low productivity will serve only limited number of markets with low productivity thresholds, while highly productive firms will be able to serve larger number of markets (Andersson *et. al.*, 2008).

Differences in the market entry thresholds arise due to many reasons, including differences in market size, intensity of competition and transport costs. Furthermore, sunk costs related to the search and

[17] The TFP measures have been calculated using extended Blundell and Bond GMM estimator as described in Van Beveren (2012) controlling for differences in export status. Please see Appendix 1 for the description of the TFP calculation methodology.

negotiation with potential customers; legal and marketing expenses, contract translations and alike tend to be market-specific and depend on the firm familiarity with a specific foreign market (Johansson and Westin, 1994; Andersson, 2007; Andersson *et al.*, 2008). Such variations in sunk entry costs imply that productivity differences between non-exporting and exporting firms may be higher when the latter target a wider range of export destinations and export products. Indeed, studies by Muuls and Pisu (2009), Castellani *et al.* (2010) and Andersson *et al.* (2008) found a positive link between firm productivity and other characteristics and the geographic and product diversification of its exporting activity.

At the same time, relatively little research so far has explored the impact of the *ex-ante* firm characteristics on its choice of the number of export markets.[18] This paper explores this aspect of the productivity-exporting nexus by using an alternative micro-econometric framework.

[Table 6 about here]

Overall, Ukrainian exporters exhibit significant heterogeneity in the number of export destinations. On average, around 50% of Ukrainian exporters export to only one destination, while only around 15% of exporters target more than 5 export markets (Table 6). The number of exporting firms declines with the number of export markets (Figure 1). These patterns in Ukrainian export data are in line with the empirical evidence on exports concentration along the country-extensive margin[19] reported by Eaton at el. (2004) for France, Muuls and Pisu (2009) for Belgium, and Bernard *et al.* (2007) for the US and Castellani *et al.* (2010) for Italy.

[Figure 1 about here]

To explore the impact of firm characteristics on its ability to penetrate larger number of export markets I estimate the model of the following form:

$$Dest_{it} =$$

$$\varphi\ (\ln TFP_{it-1} \ln Age_{it-1}, Intang_{it-1,} \ln EMP_{it-1}, \ln EMP_{it-1}^2, \qquad (2)$$

$$Industry_{it}, Region_{it} Year_{t,} GDP_{it}, FDI_{it} FDI\_match_{it}, Dest\_dummies_{it},)$$

where $Dest_{it}$ is a discrete non-negative variable indicating the number of firm export destinations; *TFP* is the estimate of the firm Total Factor Productivity calculated using the extended Blundell and

[18] Ferrante and Novelli (2012), a notable exception, address the question using cross-sectional data on Italian manufacturing firms.

[19] Mayer and Ottaviano (2007) refer to the number of countries with which firm trades as a *country-extensive margin* that can also be considered as the measure of geographical firm diversification.

Bond GMM estimator following Van Beveren (2012)[20] allowing for differences in the firm export status; *Age* is the age of the firm; *Intang* is coded 1 if the firm has nonzero intangible assets[21] (the average annual percentage of firms possessing positive intangible assets equals 14.8%); *Emp* represents firm size measured by the average annual number of enlisted employees; *Industry*, *Region* and *Year* are dummy variables indicating each of the twelve NACE Rev.1 industries, region code and year. The *GDP* variable represents the average Gross Domestic Product of the chosen export destinations[22] to control for the demand in the export market. Moreover, the *FDI* variable controls for the foreign ownership status of the firm and FDI_Match_{it} is coded 1 if at least one of the firms chosen export destinations coincides with the home country of the firm's global owner and is introduced to control for the GVC effect. Finally, $Dest\_dummies_{it}$ are introduced to control for other export destination specific factors. The model is estimated separately for low-tech and high-tech sectors to uncover sectoral differences in the impact of firm characteristics on its export choices.

The outcome variable - the number of export destinations – is a non-negative integer valued count variable, characterised by a skewed distribution and a high proportion of zeros. In fact, around 80% of the firms do not export in any given year. The conditional mean and variance are equal to 0.73 and 2.19 respectively, signalling the presence of significant over-dispersion and 'excess zeros' in the data. A possible explanation of over-dispersion and 'excess zeros' is unobserved firm heterogeneity not caught by the explanatory variables (Mullahy, 1997). An alternative explanation suggests that excess zeros emerge because export participation and export diversification decisions (i.e. the choice of the number of export destinations) are generated by the two separate probability functions (Cameron and Trivedi, 2013).

In order to account for the unobserved heterogeneity and panel structure of the data, equation (2) is estimated using the random effects negative binomial model (henceforth, RE Negbin) that allows for over-dispersion by assuming particular probability distribution (the *gamma distribution*) of the individual error terms (Jones, 2007)[23]. Furthermore, in order to account for the potential differences in the export participation and export diversification decision equation (2) is also estimated using a hurdle model that relaxes the assumption of the same stochastic process for the participation and diversification decisions. In particular, I use a hurdle model with logit binary choice model in the first stage and zero-truncated negative binomial model in the second stage. Due to the numerous complications with the implementation of the random-effects version of this type of hurdle regression,

[20] Please see Appendix 1 for the description of the TFP calculation methodology.
[21] 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 (2012) and use a dummy variable to measure intangible assets.
[22] The data on the Gross Domestic Product (GDP), based on purchasing-power-parity valuation of a country's GDP, was taken from the IMF World Economic Outlook Database, October 2015.
[23] The results of the random effect Poisson regression model are reported in Appendix 4 for comparison.

I use a pooled version of the hurdle model with firm-clustered robust standard errors and time controls (Cameron and Trivedi, 2013).[24]

4.2 Results

The results of the estimation of the RE Negbin, presented in Table 7, are mostly in line with previous studies on self-selection.[25] However, some important differences in the results emerge when distinguishing between export participation and export diversification decision.

[Table 7 about here]

The results confirm that such firm characteristics as size and possession of intangible assets increase firm's propensity to enter a larger number of export markets. Intangible assets seem to be a relatively more important export stimulus in the low-tech sectors. The possession of intangibles increases firm export diversification by approximately 15% in low-tech industries and only by 10% in the high-tech industries. The *FDI_match* variable, designed to capture the effect of the firms' participation in the GVCs, shows that firms in the low technology sectors exhibit higher propensity of exporting to the home countries of their global owners: this constitutes additional evidence that companies in the low technology sectors participate in exporting activity mostly as a part of the GVC mechanism. At the same time TFP is a significantly more important determinant of the exporting activity in the high-tech sectors, where a one unit increase in firm's TFP growth increases the range of a firm's export destinations by approximately 6%.

[Table 8 about here]

The results of the hurdle model specification presented in Table 8 show that most of the explanatory variables are important determinants of both export participation and export diversification decisions. In all sectors the age of the firm is a significant determinant of export participation but it has no relevant effect on the range of the firm's export destinations.

TFP seems to have a higher impact on the firm's ability to diversify its exports than on its propensity to export per se. On average, the impact of TFP growth on the firm's propensity to export is higher in the low-tech sectors, where a 1% increase in the TFP growth raises the firm's probability of exporting by 4%. In the high-tech sectors a 1% increase in the TFP growth raises the probability of exporting by only 2%. In the case of incumbent exporters, a 1% increase in the TFP growth increases the average number of export markets served by the firm by 0.14 in the low-tech sectors and by 0.15 - in the high tech sectors.

[24] I use STATA 14 commands *xtpoisson* and *xtnbreg* for the RE Poisson and RE Negbin regressions and *hnblogit* for the hurdle regression.
[25] Appendix 3 confirms significant self-selection effects, in the high and the low technology sectors, using the binary choice RE Probit model in line with previous studies.

The possession of intangible assets has a higher impact on the probability of export participation for the firms in the low-tech sectors rather than for the firms in the high-tech sectors. At the second stage, however, the possession of intangible assets increases the range of target export markets by 0.3 for the high-tech firms, and only by 0.16 for the low-tech firms. Finally, the *FDI_match* variable has a significant impact on export diversification only for firms in the low-tech sectors: once again this confirms a higher propensity of these firms to become exporters as a part of the GVC.

Overall, the results show that ex-ante productivity improvements are important determinants of exporting in both the high and the low-tech sectors. In the low-tech sectors, productivity improvements are more important for the firm's propensity to engage into exporting, while in the high-tech sectors they are relatively more important for the ability of the firm to penetrate larger number of export markets.

5 Learning-by-exporting: the role of industry and export destination

5.1 Econometric Modelling

This section estimates learning-by-exporting (LBE) effect for Ukrainian manufacturing firms for the full spectrum of the firm's export participation decisions. While most of the studies concentrate on the impact of exporting on the productivity of the new entrants, this paper uncovers the LBE effect simultaneously for entering, exiting and switching firms distinguishing between various types of industries and export destinations. Several recent empirical studies have found a substantial degree of heterogeneity of the LBE effects in different export markets (Damijan *et al.*, 2004; De Loecker, 2007; Muuls and Pisu, 2009). However, to the best of my knowledge, this is the first study to address the link between the technological intensity of the industry and its ability to benefit from exporting to specific export destinations.

As pointed out by the previous empirical literature, the estimation of the LBE effect at the micro level is often complicated by the *selection bias*. The bias occurs because potential exporters may be systematically different from their counterparts in certain unobservable intrinsic characteristics that make them superior to non-exporting firms and are correlated with their export participation decision.

The standard test of the self-selection hypothesis on Ukrainian manufacturing data confirms self-selection of more productive firms into exporting.[26] Hence a simple comparison of the average productivities between exporters and non-exporters may result in biased estimates of the treatment effect.[27]

[26] The results of the *RE Probit* model, presented in Appendix 3, confirm that firm TFP, as well as size, age and intangible assets increase firm's propensity to export.
[27] See Heckman and Navarro-Lozano (2004) for a formal discussion.

To obtain consistent estimates of the productivity gains from exporting we need to obtain a counterfactual that would show the evolution of firm productivity had it not stared exporting, in other words any simultaneous relationship between export decision and productivity gains has to be removed. A number of estimation techniques try to address the issue of the correlation between the unobserved firm productivity and its export decision. The most popular ones include *matching* methods that compare exporters only with the "control" groups of domestic firms with similar characteristics (Girma *et. al.*, 2004); the *difference-in-differences* (DID) methodology (De Loecker, 2007), the Heckman two-stage procedure and instrumental variables (IV) (Damijan *et al.*, 2004; Wilhelmsson and Kozlov, 2007; Harris and Li, 2012).

While all of the above techniques address selectivity issues, the choice of the estimator depends on the specific selection process and data at hand. For example, the application of the two-stage growth accounting approach leaves a possibility of inefficient estimates and omitted variables problems (Wang and Schmidt, 2002). At the same time, the Heckman approach may be less suitable for panel data, when the effect of exporting is estimated with lead and lag terms of export participation decision, as the inclusion of the lead and lag terms of export status would also require the inclusion of an appropriate number of selectivity correction terms from the first stage. At the same time, matching methods might not be an optimal choice for unbalanced panel data, when export entry and exit occur at different points in time (Harris and Li, 2012).

Taking into account the nature of the data this paper adopts the *instrumental variables* (IV) approach, which requires finding appropriate instrument variables that affect the treatment decision (decision to export) but do not directly influence the outcome (TFP). The main problem with the IV approach is the availability of appropriate instruments, which sometimes might be limited due to data issues and the economic mechanisms that determine the relationship between the treatment and the outcome (Angrist and Krueger, 2001). The second problem with the IV approach is related to the heterogeneity of the treatment effects, when instead of estimating an average impact of treatment effect on treated, the IV model will estimate a Local Average Treatment Effect (LATE). In this case, we will get the 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 1997).

The instruments previously used in the literature to address export-related selection bias problem include the *age* of the firm and its *intangible assets*. The available empirical evidence suggests that these variables have no significant impact on the real gross output, while having significant impact on the ability of the firm to overcome export entry barriers (Damijan *et. al.*, 2004; Harris and Li, 2012).

Taking into account the panel nature of the data and the available potential instruments, I estimate the dynamic panel data (DPD) production function including in the instrument set both the age of the firm and the dummy for intangible assets. The model includes a full spectrum of firm export choices across export regions, which allows me to estimate the heterogeneity of productivity spillovers across export destinations. In particular, I estimate the following equation:

$$lnY_{it} = \alpha_0 + \alpha_1 lnY_{i,t-1} + \sum_{j=1}^{3} \alpha_{2j} x_{jit} + \sum_{j=1}^{3} \alpha_{3j} x_{jit-1} + \sum_{l=1}^{4} \beta_l D_l + \sum_{l=1}^{4} \sum_{j=1}^{3} \delta_{lj} (D_l x_{jit})$$

$$\sum_{m=1}^{3} \sum_{s=-1}^{1} \theta_{ms} D_{imt-s} + \sum_{n=1}^{3} \vartheta_n DEST_{nt} + \sum_{n=1}^{3} \sum_{m=1}^{3} \sum_{s=-1}^{1} \mu_{nms}\, DEST_{nt} D_{mit-s} \qquad (3)$$

$$\sum_{n=1}^{28} \pi_n REG_n + \sum_{p=1}^{12} \sigma_p IND_p + \sum_{t=1}^{6} \tau_t YEAR_t$$

$$\eta_i + \gamma_t + \omega_{it}$$

In equation (3) Y is the firm's gross real output, x_1 represents the logarithm of the intermediate inputs; x_2 is the logarithm of the capital stock; x_3 is the logarithm of total employment; D_l is a set of dummy variables indicating the firm's export status. These variables include the following groups: *Exp_never* (benchmark group), *Exp_always* (D_1); *Exp_entry* (D_2); *Exp_exit* (D_3); *Exp_both* (D_4).[28] By introducing interaction terms between export status controls and factor inputs $D_l x_{jit}$, I allow for different production functions for firms with different export status (Harris and Li, 2012). For the firms that change their export status during the observed period I introduce additional time-specific control variables (D_{imt}) that capture the impact of the change in the firm export status. These variables include $Entry_{it}$, $Exit_{it}$ and $Switcher_{it}$ and change their values from zero to one in the period when firm i commences (D_{i1t}) or ceases exporting (D_{i2t}), or ceases exporting after previous entry (D_{i3t}) during the 2000 – 2005 period. Variables $DEST_{nt}$ are designed to capture the impact of export destination. I distinguish between four main export regions including Tax Heavens[29] (benchmark group), Emerging Markets, CIS countries and Advanced Economies.[30] To estimate the effect of exporting to specific regions, these destination control variables are interacted with the time-sensitive export status dummy variables D_{imt} ($Entry_{it}$, $Exit_{it}$ and $Switcher_{it}$). These variables are introduced in the model with a lead and lagged term. Finally, the dummy variables REG_n, IND_p and $YEAR_t$ indicate the region, industry and year dummies respectively. The composite error term has three elements: η_i captures the unobserved time-invariant firm specific effect; γ_t affects all firms for the period t; ω_{it} is a firm-specific

[28] I follow Harris and Li (2012) 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 during the observed time period, those that exited and lastly, those that changed their export status more than once. The base group includes firms that never exported during the observed period.

[29] Tax Heaven controls were constructed using the information provided by the Tax Justice Network: http://www.taxjustice.net/

[30] Destination dummies were constructed using IMF World Economic Outlook country classification: https://www.imf.org/external/pubs/ft/weo/2015/02/weodata/groups.htm

productivity component that affects firm i in period t. Notice that in case there are no measurement errors the firm-specific productivity component reduces to a serially-uncorrelated random productivity shock and $\omega_{it} \sim MA(0)$, otherwise $\omega_{it} \sim MA(1)$ (Blundell and Bond, 2000).

Equation (3) is estimated using the extended Generalized Method of Moments (GMM) estimator available in STATA 9-14 (Blundell and Bond, 2000). Unlike standard IV estimators, the system GMM approach uses lagged values in both the levels and the first differences of the potentially endogenous variables as instruments and allows for a first-order autoregressive error term, which significantly improves the parameter estimates (Van Beveren, 2012).

5.2 Results

The results of the destination specific LBE effect along with the diagnostic tests are shown in Table 9.[31] The results are reported separately for the high-tech and low-tech industry sub-groups to assess the role of the industry technological intensity in the ability of firms to absorb the productivity benefits from exporting.

As discussed, the instrument set for the equation (3) included age and intangible assets and the lagged values and first differences of the potentially endogenous regressors. The validity of the chosen instruments is supported by the results of the RE Probit model,[32] where the age and intangible assets appear to be significant determinants of the firm's exporting activity. For both industry sub-groups the model shows no significant second order autocorrelation (as indicated by the AR(1) and AR(2) test statistics) and passes the Hansen test, indicating the adequacy of the instruments used.

In terms of the parameters, there are three sets of estimates that capture the impact of exporting on productivity. The first set is the *Exp_entry* variables that should deliver significant positive estimates for the first time entrants in period *t* and *t+1*. The second set includes the *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, and should potentially deliver significant positive estimates in periods *t* and *t+1.* The structure of the model allows to disentangle the productivity effect of export participation for the firms that export to the markets of higher development levels (advanced economies), markets of lower development levels (emerging markets) and markets of similar development levels (CIS countries). Finally, the structure of the model allows for the simultaneous entry and exit from the multiple export destinations.

[Table 9 about here]

[31] The complete set of results can be found in Appendix 5.
[32] The complete set of results can be found in Appendix 3.

The results on the learning-by-exporting effect are different for the high and low-tech industry groups. Firms in both high and low technology sectors experience significant positive post-entry productivity effects when entering into the advanced markets. However, the effect is stronger for firms in low-tech industries, while for firms in the high-technology sectors the effect seems to be weaker and short lived. Such results indicate the fact that Ukrainian firms in low technology sectors are initially further away from the technology frontier and experience more pronounced productivity benefits from the access to the better technologies of the advanced countries. At the same time, firms in the high technology sectors exhibit significant productivity losses when exiting from both advanced and emerging markets, while the firms in the low-tech industries do not seem to experience any significant negative productivity shocks associated with the termination of exporting activity. Finally, the firms that enter and exit export markets more than once during the observed time period experience positive productivity gains only in the high technology sectors. Overall, the productivity effect associated with the beginning and termination of exporting activity appears to be more pronounced in the high-tech sectors.

The general nature of the results is in line with other studies that found significant evidence of the LBE effect. Most of the productivity improvements are associated with the entry into to the advanced export markets, while termination of the exporting activity is associated with productivity losses irrespective of the export destination.

At the same time, some important differences in the results of the current study have to be highlighted. First of all, the LBE effect has different implications for the productivity of the firms in the high-tech and low-tech sectors. The studies that attempted to explore the role of export destination in the export-related productivity improvements using aggregate manufacturing data pointed out significant industry heterogeneity in the LBE effect (De Loecker, 2007; Damijan *et al.*, 2004; Harris and Li, 2012). However, no attempt has been made so far to explore whether the effect of exporting on the productivity of the firm depends on the technology intensity of the industry where the firm operates. The main contribution of the current study, hence, lies in the attempt to single out the role of the industry technological intensity and the export destination in the learning-by-exporting effect. Furthermore, the use of the dynamic system GMM approach allows us to account for self-selection and the endogeneity that arises when the two-stage growth-accounting approach is used (Harris, 2005).

The results confirm that the empirical analysis of the LBE effect should explicitly account for industry heterogeneity, as the ability to internalize new knowledge and adopt new technologies might vary among the firms in the high-tech and low-tech sectors. Thus, the systematic distinction between technology and the capital intensity of different industries should improve the results of future empirical studies looking for the empirical evidence of the LBE effect.

6 Discussion and Concluding Remarks

This paper presents an attempt to estimate the impact of exporting activity on a firm's performance using micro-level data on Ukrainian manufacturing firms over the period 2000-2005 distinguishing among export destinations and industrial technological intensity.

The first part of the paper explores the impact of firm characteristics on the number of potential export destinations. In order to account for the discrete non-negative nature of the outcome variable, the issue is addressed with the use of the count data models. The results of the analysis reveal that the size of the firm is an important determinant of its ability to penetrate a larger number of export markets. At the same time, the age of the firm is a significant determinant of export participation in all sectors, while it does not have any significant effect on the range of export destinations for the incumbent exporters. Intangible assets have a higher impact on the probability of export participation for the firms in the low-tech sectors while, conditional on entrance, the possession of intangibles is relatively more important for the export diversification of the high-tech firms. Total Factor Productivity, in turn, has a high impact on the propensity of firms to enter exporting, as well as on their propensity to widen the range of export destinations in both high and low-tech sectors. Finally, the results reveal that firms with low technological intensity exhibit a higher propensity to export to the home countries of their global owners, providing additional evidence that companies in the low technology sectors participate in exporting activity as a part of the GVC mechanism.

The second part of the analysis studies the post-entry productivity effects of exporting (*learning-by-exporting effect*) for the full spectrum of the firm export participation decisions across export destinations. The analysis is implemented with the help of the dynamic system GMM estimator (Blundell and Bond, 2000) to account for endogeneity and sample selection.

The results of the analysis partially confirm the existence of positive productivity shocks in periods t and $t+1$ for the new exporters that enter advanced markets; negative productivity shocks in periods t and $t+1$ for the firms that cease their exporting activity; and positive productivity gains for the firms that enter and exit advanced and emerging markets more than once.

The results, however, are not universal across industries. On average, firms in the low-technology industries are much less sensitive to the changes in their export status, while technology-intensive firms experience more consistent export-related productivity shocks. Thus, when exporting is targeted at the advanced export markets, firms in both high and low-tech sectors experience significant positive productivity shocks. However, irrespective of the destination market, firms in high-tech sectors experience negative productivity shocks when ceasing exporting; on the other hand, low-tech firms that terminate the exporting activity experience no significant negative productivity shock of any kind.

The literature suggests several reasons that explain the weak evidence on the learning-by-exporting effect in sectors with low technology intensity. First of all, exporters of low-tech products and raw materials rely mainly on the low-cost advantage rather than on new technologies developed through R&D investment. Furthermore, firms in high-technology sectors usually possess superior assets, such as intangibles and human capital, and managerial practices that serve as important determinants of their ability to overcome export entry barriers (Kogut and Zander, 1996). These assets also improve the ability of the firm to absorb new knowledge and adopt new technologies available in the export markets: this mechanism would imply stronger export-related productivity shocks for the exporters in the high-technology industries.

The main contribution of the current study, hence, lies in the attempt to single out the role of the industry technological intensity and export destination in the empirical analysis of the learning-by-exporting effect. Furthermore, the use of the dynamic system GMM approach allows us to account for self-selection and endogeneity that arise in the two-stage estimation approach.

The results suggest that the empirical analysis of the learning-by-exporting effect should explicitly account for industry heterogeneity. Indeed, the ability to internalize new knowledge and adopt new technologies might vary among firms in high-technology and low-technology sectors. Thus, a systematic distinction between the technological and capital intensity of different industries should improve the results of future empirical studies looking for the empirical evidence of the LBE effect.

The proposed analysis may also have relevant implications for the policy makers, particularly of developing and transition economies. Government policies, in fact, are often aimed at increasing R&D investment and at stimulating the development of the technology-intensive sectors. According to the results provided, these policies would increase the ability of domestic firms to overcome the export-entry barriers, as well as diversifying their exports across a wider range of export destinations. Furthermore, there is scope for tailoring policy interventions in an attempt to make them more effective. Stimulating policies may, in fact, single out the firms in the low-tech sectors with the potential to improve their knowledge base inducing them to switch status: this, in turn, would further raise their ability to absorb export-related productivity benefits.

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Appendix 1. Total Factor Productivity Estimation.

I follow Blundell and Bond (2000) and assume a production function (measured as gross output) to be a function of the input factors and the productivity of the firm. To measure TFP I first estimate a Cobb-Douglas production function presented in equation (6) for each of the twelve industries to obtain the elasticities of output with respect to inputs.

$$y_{it} = \sum_{i=1}^{4} \alpha_i x_{it} + \sum_{j=1}^{28} \beta_j REG_j + \sum_{t=1}^{T} \gamma_t YEAR_t + \sum_{n=1}^{12} \delta_n IND_n + \eta_i + \upsilon_{it} + m_{it}$$

$$\upsilon_{it} = \rho \upsilon_{it-1} + e_{it}, \qquad |\rho| < 1 \tag{6}$$

$$e_{it}, m_{it} \sim MA(0)$$

In equation (6) y, x_1, x_2, x_3 and x_4 stand for the logarithms of output, employment, intermediate inputs, capital stock and a dummy variable indicating export status of the firm i at time t. Variables REG_j, IND_n and $YEAR_t$ indicate the regions, industries and year controls respectively The composite error term has three elements: η_i unobserved time-invariant firm specific effect; υ_{it} potentially autoregressive (productivity) shock; m_{it} serially uncorrelated measurement error. Intuitively υ_{it} might be associated with such variables as managerial ability of the firm, expected defect rates in manufactured goods or expected amount of rainfall; while e_{it} represents unexpected deviation from the expected levels of all the factors mentioned earlier.

The TFP measures can be further recovered from (6) after the factor elasticities have been estimated. However, since the TFP estimates are further used to assess the impact of the firm TFP on its export participation decisions, I control for the firm export status when estimating equation (6) to avoid obtaining inefficient and biased estimates of the equation (2) in section 4 (Newey and McFadden, 1999, Wang and Schmidt, 2002).[33]

In order to account for a number of methodological issues related to the TFP estimation equation (6) is estimated using extended GMM estimator (system-GMM estimator by Blundell and Bond, 2000), that uses a mixture of lagged values and first-differences as instruments for the potentially endogenous repressors and assumes a first-order autoregressive error-term. I also use *age* and *intangible assets* as additional instruments for the firm's export participation decision.

[33] Van Beveren (2012); 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.

Appendix 2. OECD ISIC Rev. 3 Classification of Manufacturing Industries based on Technology.[34]

OECD Category	Industries
Low Technology Industries	Food Products, Beverages and Tobacco Textiles, Leather, Fur, Footwear Wood and Wood Products Paper, Paper Products, Printing, Publishing Manufacturing, n.e.c.; Recycling
Medium-Low Technology Industries	Basic metals and fabricated metal products Other non-metallic mineral products Coke, refined petroleum products and nuclear fuel Rubber and plastics products
Medium-High Technology Industries	Machinery and equipment, n.e.c. Electrical machinery and apparatus, n.e.c Motor vehicles, trailers and semi-trailers Chemicals excluding pharmaceuticals Railroad equipment and transport equipment, n.e.c
High Technology Industries	Medical, precision and optical instruments Radio, TV and communications equipment Office, accounting and computing machinery Pharmaceuticals Aircraft and spacecraft

[34] Source: http://www.oecd.org/sti/ind/48350231.pdf

Appendix 3. RE Probit model estimation results. Marginal effects.

Industry classification	$\ln TFP_{t-1}$	$\ln Age_{t-1}$	$\ln Emp_{t-1}$	$\ln Emp^2_{t-1}$	$Intange_{t-1}$	No. Obs.	No of Groups
Low-Technology Industries	0.269***	1.962***	1.554***	0.0007	0.476***	79,182	27,118
	(0.0415)	(0.278)	(0.0526)	(0.0030)	(0.0604)		
High-Technology Industries	0.230***	1.241***	1.104***	0.0004	0.323***	24,859	9,055
	(0.00970)	(0.222)	(0.0391)	(0.0003)	(0.0554)		

Note: Dependent variable: firm export status coded 1 if a firm has exported in any given year. Robust standard errors in parentheses; ***- significant at 1% level; **- significant at 5% level; *- significant at 10% level. The model includes *Industry*, *Region* and *Year* dummies. *RE Probit*: Random Effects Probit Model.

Appendix 4. Firm heterogeneity and Export Choices, RE Poisson model.

	Poisson, RE		Poisson, RE: Marginal Effects	
	Low-Tech Sectors	High-Tech Sectors	Low-Tech Sectors	High-Tech Sectors
$\ln TFP_{it-1}$	0.034**	0.094***	0.040***	0.058***
	(0.017)	(0.005)	(0.020)	(0.003)
$\ln Age_{it-1}$	0.371***	0.157	0.433***	0.097
	(0.125)	(0.117)	(0.147)	(0.072)
$Intang_{it-1}$	0.134***	0.098***	0.157***	0.061***
	(0.030)	(0.031)	(0.035)	(0.019)
$\ln EMP_{it-1}$	0.264***	0.326***	0.309***	0.201***
	(0.014)	(0.015)	(0.019)	(0.011)
$\ln EMP^2_{it-1}$	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
GDP_{it}	-0.000	0.003***	-0.000	0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
FDI_t	0.044	0.060	0.052	0.037
	(0.037)	(0.050)	(0.043)	(0.030)
FDI_match_t	0.173***	0.082*	0.202***	0 .051*
	(0.040)	(0.46)	(0.048)	(0.028)
REG_t	Yes	Yes	Yes	Yes
$YEAR_t$	Yes	Yes	Yes	Yes
IND_t	Yes	Yes	Yes	Yes
$DEST\_dummies_t$	Yes	Yes	Yes	Yes
No. of obs.	79,182	24,859	79,182	24,859
No. of firms	27,118	9,055	27,118	9,055
Log Likelihood	-20352.98	-9255.1192	-20352.98	-9255.1192
BIC	41010.51	18783.5	41010.51	18783.5
LR Test	3465.53	1399.70	3465.53	1399.70

Note: Dependent variable: number of export destinations ranging from zero to 49. Cluster robust standard errors in parentheses; ***- significant at 1% level; **- significant at 5% level; *- significant at 10% level. All regressions include *Industry*, *Region* and *Year* dummies as controls. Marginal effects were calculated using *margins* command in STATA 14.

Appendix 5. System GMM Production Function estimates, Ukraine 2000-2005.

Independent variables	Low-technology industries	High-technology industries
Ln k	0.022	0.275**
	(0.091)	(0.134)
Ln k_{t-1}	0.007	-0.223**
	(0.079)	(0.121)
Ln m	0.746***	0.552***
	(0.075)	(0.087)
Ln m_{t-1}	-0.639***	-0.190***
	(0.071)	(0.067)
Ln l	0.417***	0.639***
	(0.143)	(0.177)
Ln l_{t-1}	-0.468***	-0.421***
	(0.128)	(0.144)
Ln output $_{t-1}$	0.870***	0.602***
	(0.081)	(0.072)
Ln K * Always Exporter	0.170	-0.129
	(0.199)	(0.091)
Ln K * Entrant	-0.143*	-0.122
	(0.086)	(0.094)
Ln K * Exitor	-0.025	-0.026
	(0.085)	(0.086)
Ln K * Switcher	-0.014	-0.067
	(0.062)	(0.099)
Ln M * Always Exporter	-0.194**	-0.158***
	(0.096)	(0.050)
Ln M * Entrant	-0.098	-0.251***
	(0.081)	(0.084)
Ln M * Exitor	0.002	-0.053
	(0.064)	(0.072)
Ln M * Switcher	0.023	-0.079
	(0.061)	(0.079)
Ln L * Always Exporter	-0.264	-0.016
	(0.287)	(0.107)
Ln L * Entrant	0.381***	0.101
	(0.157)	(0.151)
Ln L * Exitor	-0.012	-0.325**
	(0.133)	(0.151)
Ln L * Switcher	0.021	-0.266*
	(0.111)	(0.158)
Always exporter	1.755	0.165
	(1.426)	(0.522)
Entrant	1.687***	-0.266
	(0.705)	(0.709)
Exitor	0.092	1.495***
	(0.635)	(0.680)
Switcher	-0.078	1.139*
	(0.508)	(0.751)
$Entry_{t+1}$	-1.011	-0.509
	(0.743)	(1.993)
$Entry_{t}$	-0.058	-0.400**
	(0.203)	(0.201)

$Entry_{t-1}$	-0.157	0.017
	(0.186)	(0.154)
$Exit_{t+1}$	-0.031	1.187
	(1.113)	(1.131)
$Exit_{t}$	0.109	0.475**
	(0.114)	(0.247)
$Exit_{t-1}$	0.052	-0.050
	(0.142)	(0.230)
$Switcher_{t+1}$	0.502	-0.445
	(0.856)	(1.311)
$Switcher_{t}$	-0.132	-0.257
	(0.167)	(0.175)
$Switcher_{t-1}$	0.205	-0.436
	(0.193)	(0.428)
$Entry_{t+1}$ * Advanced Economies	1.232*	-0.960
	(0.685)	(1.277)
$Entry_{t}$ * Advanced Economies	0.139	0.303*
	(0.175)	(0.182)
$Entry_{t-1}$ * Advanced Economies	0.051	-0.072
	(0.161)	(0.131)
$Exit_{t+1}$* Advanced Economies	-0.711	-0.697
	(0.845)	(1.108)
$Exit_{t}$ * Advanced Economies	-0.090	-0.354*
	(0.088)	(0.222)
$Exit_{t-1}$* Advanced Economies	-0.009	0.118
	(0.107)	(0.202)
$Switcher_{t+1}$* Advanced Economies	-0.604	1.055
	(0.793)	(1.259)
$Switcher_{t}$* Advanced Economies	0.125	0.246*
	(0.156)	(0.141)
$Switcher_{t-1}$* Advanced Economies	-0.147	0.568
	(0.163)	(0.411)
$Entry_{t+1}$ * Emerging Market	0.097	0.715
	(1.405)	(1.330)
$Entry_{t}$ * Emerging Market	-0.149	0.183
	(0.181)	(0.209)
$Entry_{t-1}$ * Emerging Market	0.047	0.018
	(0.187)	(0.137)
$Exit_{t+1}$* Emerging Market	-1.591	-1.533*
	(1.481)	(0.882)
$Exit_{t}$ * Emerging Market	-0.175	-0.555**
	(0.133)	(0.270)
$Exit_{t-1}$* Emerging Market	-0.119	0.413
	(0.144)	(0.287)
$Switcher_{t+1}$* Emerging Market	-1.128	0.911
	(1.411)	(0.924)
$Switcher_{t}$* Emerging Market	0.178	0.351**
	(0.158)	(0.171)
$Switcher_{t-1}$* Emerging Market	-0.325*	0.505
	(0.199)	(0.358)
$Entry_{t+1}$ * CIS	0.534	1.444
	(0.875)	(1.937)
$Entry_{t}$* CIS	0.038	0.256

	(0.204)	(0.183)
$Entry_{t-1}$* CIS	0.113	-0.102
	(0.177)	(0.148)
$Exit_{t+1}$* CIS	1.221	-0.831
	(1.009)	(1.202)
$Exit_{t}$* CIS	-0.071	-0.415*
	(0.097)	(0.229)
$Exit_{t-1}$* CIS	-0.028	-0.013
	(0.124)	(0.214)
$Switcher_{t+1}$* CIS	-0.523	-0.062
	(0.921)	(1.180)
$Switcher_{t}$* CIS	0.135	0.142
	(0.157)	(0.152)
$Switcher_{t-1}$* CIS	-0.171	0.372
	(0.161)	(0.425)
Advanced Economy	-0.066	-0.057
	(0.113)	(0.132)
CIS	0.151	0.126
	(0.108)	(0.118)
Emerging market	0.071	0.150
	(0.122)	(0.120)
Industry Dummies	Yes	Yes
Time dummies	Yes	Yes
Region Dummies	Yes	Yes
Foreign Ownership Status	Yes	Yes
No of obs.	57319	25798
No of groups.	22078	9035
AR(1) z-statistics	-15.18***	-13.88***
AR(2) z-statistics	0.94	0.50
Hansen Test	127.72	105.02

Note: Please refer to Appendix 2 for the details of the OECD technology intensity industry classification. The estimation uses the *xtabond2* command in STATA 14: instrument set includes the right hand side variables of the model; age and a dummy indicating possession of intangible assets. Robust standard errors in parentheses; ***- significant at 1% level; **- significant at 5% level; *- significant at 10% level.

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

Year	2000	2002	2003	2005	Average
Number of firms	31,540	35,811	36,963	37,831	35,536
Number of exporters	4,719	5,055	5,430	5,672	5,219
Share of Exporters	15.0%	14.1%	14.7%	15.0%	14.7%
Number of entrants	--	881	1,123	1,441	1,148
Number of quitters	---	1,190	1,105	1,011	1,102
Entry rate	__	2.5%	3.0%	3.8%	3.1%
Exit rate	__	3.3%	3.0%	2.7%	3.0%

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

	2000	2003	2005
Output (Gross Output)	3340.05 (58321.74)	5165.02 (90920.87)	6785.81 (125443.25)
Employment	91.30 (645.31)	69.52 (640.17)	47.06 (334.07)
Materials	2188.84 (40897.19)	3508.90 (66129.34)	3836.41 (101161,79)
Capital	3776.71 (35118.78)	2916.31 (33222.91)	2125.57 (22152.11)

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

Table 3. Export Participation by Industry Groups, 2000-2005 average.

	Low-Technology Industries	Medium-Low-Technology Industries	Medium-High-Technology Industries	High-Technology Industries
Number of firms	16,276.83	6,287.17	5,614.83	4,226.33
Share of exporters	8.1%	12.1%	16.5%	13.3%

Table 4. Exporters’ premium in Ukrainian firms.

	Low and Medium-Low Technology Firms		High and Medium-High Technology Firms	
Firm Characteristic (x)	**β**	**R^2**	**β**	**R^2**
Average wage (log)	0.3418	0.32	0.2219	0.27
Labour productivity (log)	1.0189	0.22	0.7491	0.28
Sales per worker (log)	1.1774	0.18	0.9370	0.07
Capital per worker (log)	0.5481	0.11	0.5986	0.08
Investment per worker (log)	0.7390	0.09	0.7202	0.06
Employment (log)	1.9226	0.25	1.9353	0.16

Note: All coefficients are significant at 1% level. All regressions control for the industry and firm size effect, except for the employment regression. The monetary values are deflated using Ukrainian Office of National Statistics industry deflators.

Table 5. Two-sample Kolmogorov-Smirnov tests on the distribution of TFP by industry sub-groups, Ukraine, 2000-2005 average.

OECD Industry Groups by Technology Intensity	All exporters	All non-exporters
Low and Medium-Low-Technology Industries	-0.017*	0.029***
Medium-High and High Technology Industries	-0.001	0.254***

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

Table 6. Distribution of Ukrainian Exporting Firms by the Number of Export Destinations and Industry Groups, 2000-2005 average.

Number of Export Destinations	Low-Technology Industries	Medium-Low-Technology Industries	Medium-High-Technology Industries	High-Technology Industries
1	54%	50%	44%	47%
2	20%	19%	19%	20%
3	10%	10%	10%	10%
4	5%	5%	7%	7%
5+	10%	16%	20%	15%

Table 7. Firm heterogeneity and Export Choices, RE Negbin model.

	Negative Binomial, RE		Marginal Effects	
	Low-Tech Sectors	High-Tech Sectors	Low-Tech Sectors	High-Tech Sectors
$\ln TFP_{it-1}$	0.0272* (0.0166)	0.0929*** (0.00581)	0.040** (0.020)	0.057*** (0.003)
$\ln Age_{it-1}$	0.402*** (0.109)	0.193* (0.120)	0.432*** (0.148)	0.119* (0.071)
$Intang_{it-1}$	0.143*** (0.0265)	0.0986*** (0.0323)	0.157*** (0.036)	0.060*** (0.002)
$\ln EMP_{it-1}$	0.267*** (0.0135)	0.315*** (0.0161)	0.308*** (0.020)	0.194*** (0.011)
$\ln EMP_{it-1}^2$	-0.0001 (0.0015)	0.008* (0.0005)	-0.000 (0.000)	0.001* (0.000)
GDP_{it}	0.0004 (0.0005)	0.003*** (0.0007)	-0.000 (0.000)	0.001*** (0.000)
FDI_t	0.0469 (0.0347)	0.0684 (0.0512)	0.052 (0.043)	0 .042 (0.031)
FDI_match_t	0.178*** (0.038)	0.0835* (0.0484)	0.203*** (0.048)	0.051* (0.029)
REG_t	Yes	Yes	Yes	Yes
$YEAR_t$	Yes	Yes	Yes	Yes
IND_t	Yes	Yes	Yes	Yes
$DEST\_dummies_t$	Yes	Yes	Yes	Yes
No. of obs.	79,182	24,859	79,182	24,859
No. of firms	27,118	9,055	27,118	9,055
Log Likelihood	-20346.407	-9219.2242	-11049.345	-9255.1192
BIC	41008.64	18721.84		
LR Test	2512.13	891.28		

Note: Dependent variable: number of export destinations ranging from zero to 49. Cluster robust standard errors in parentheses; ***- significant at 1% level; **- significant at 5% level; *- significant at 10% level. All regressions include *Industry*, *Region* and *Year* dummies as controls. Marginal effects were calculated using *margins* command in STATA 14.

Table 8. Hurdle Model, Marginal Effects.

	Pooled Hurdle Model, First Stage		Pooled Hurdle Model, Second Stage	
	Low-Tech Sectors	**High-Tech Sectors**	**Low-Tech Sectors**	**High-Tech Sectors**
$\ln TFP_{it-1}$	0.037*** (0.008)	0.017*** (0.001)	0.135** (0.058)	0.146*** (0.016)
$\ln Age_{it-1}$	0.223*** (0.043)	0.043*** (0.009)	0.207 (0.339)	0.091 (0.286)
$Intang_{it-1}$	0.091*** (0.011)	0.012*** (0.002)	0.160** (0.086)	0.304*** (0.087)
$\ln EMP_{it-1}$	0.195*** (0.007)	0.055*** (0.003)	0.470*** (0.036)	0.625*** (0.046)
$\ln EMP_{it-1}^2$	-0.005 (0.008)	-0.001 (0.002)	-0.001 (0.001)	0.001* (0.000)
FDI_t	0.265*** (0.023)	0.029*** (0.007)	-0.075 (0.112)	0.111 (0.160)
FDI_match_t	No	No	0.264** (0.125)	0.144 (0.127)
GDP_{it}	No	No	-0.019*** (0.001)	-0.022*** (0.001)
REG_t	Yes	Yes	Yes	Yes
$YEAR_t$	Yes	Yes	Yes	Yes
IND_t	Yes	Yes	Yes	Yes
$DEST\_dummies_t$	No	No	Yes	Yes
No. of obs.	79,182	24,859	12,293	7,304
Log Likelihood	-18157.243	-11822.985	-16189.66	-10223.983
Pseudo R squared	0.32	0.35	0.21	0.23

Note: Dependent variable: number of export destination ranging from zero to 49. Cluster robust standard errors in parentheses; ***- significant at 1% level; **- significant at 5% level; *- significant at 10% level. Destination dummies, FDI_match_{it} and GDP_t are included only in the second stage of the model. Marginal effects were calculated using *margins* command in STATA 14.

Table 9. The 'Learning-by-exporting' effect for Ukrainian Manufacturing Industries by destination, 2000-2005.

	Emerging Markets		Commonwealth of Independent States		Advanced Economies	
	Low-Tech Sectors	High-Tech Sectors	Low-Tech Sectors	High-Tech Sectors	Low-Tech Sectors	High-Tech Sectors
Exp_entry_{t+1}	0.097 (1.405)	0.715 (1.330)	0.534 (0.875)	1.444 (1.937)	1.232* (0.685)	-0.960 (1.277)
Exp_entry_{t}	-0.149 (0.181)	0.183 (0.209)	0.038 (0.204)	0.256 (0.183)	0.139 (0.175)	0.303* (0.182)
Exp_entry_{t-1}	0.047 (0.187)	0.018 (0.137)	0.113 (0.177)	-0.102 (0.148)	0.051 (0.161)	-0.072 (0.131)
Exp_exit_{t+1}	-1.591 (1.481)	-1.533* (0.882)	1.221 (1.009)	-0.831 (1.202)	-0.711 (0.845)	-0.697 (1.108)
Exp_exit_{t}	-0.175 (0.133)	-0.555** (0.270)	-0.071 (0.097)	-0.415* (0.229)	-0.090 (0.088)	-0.354* (0.222)
Exp_exit_{t-1}	-0.119 (0.144)	0.413 (0.287)	-0.028 (0.124)	-0.013 (0.214)	-0.009 (0.107)	0.118 (0.202)
Exp_both_{t+1}	-1.128 (1.411)	0.911 (0.924)	-0.523 (0.921)	-0.062 (1.180)	-0.604 (0.793)	1.055 (1.259)
Exp_both_{t}	0.178 (0.158)	0.351** (0.171)	0.135 (0.157)	0.142 (0.152)	0.125 (0.156)	0.246* (0.141)
Exp_both_{t-1}	-0.325* (0.199)	0.505 (0.358)	-0.171 (0.161)	0.372 (0.425)	-0.147 (0.163)	0.568 (0.411)
No. of Obs	57319	25798	57319	25798	57319	25798
No of Groups	22078	9035	22078	9035	22078	9035
Ar (1) z-stat	-15.18***	-13.88***	-15.18***	-13.88***	-15.18***	-13.88***
Ar (2) z-stat	0.94	0.50	0.94	0.50	0.94	0.50
Hansen test	127.72	105.02	127.72	105.02	127.72	105.02

Note: The estimation uses the *xtabond2* command in STATA 14: instrument set includes the right hand side variables of the model; age and a dummy indicating possession of intangible assets. Robust standard errors in parentheses; ***- significant at 1% level; **- significant at 5% level; *- significant at 10% level.