Exporting and Firm Performance: Evidence from Ukrainian Economy*

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Abstract

Recent theoretical models of firm production behavior (Melitz 2003, Melitz and Ottaviano 2005) imply higher productivity among exporters as compared to non-exporting firms. Sunk costs of exporting lead to self-selection of firms into foreign markets, hence only the most productive firms will export. In this paper I examine the empirical evidence of the firm production behavior models' implications using an unbalanced panel of Ukrainian manufacturing firms and applying the semi-parametric estimation technique developed by Olley and Pakes (1996) to estimate TFP. Similarly to other empirical studies, I find that exporting firms are, on average, more productive. As a robustness check I use Levinsohn and Petrin (2003) method to estimate TFP. Both methods produce very similar distributions of TFP across exporting and non-exporting firms. In line with previous research I try to distinguish between self-selection and learning-by-doing. For this purpose I apply matching, which is widely used in micro-level studies. Matching appears to demonstrate that even after controlling for self-selection, exporters seem to be more productive. However, results should be interpreted with caution since productivity differential attributed to exporting may be caused by unobservable characteristics, thus leaving room for further investigation.

JEL codes: D24, L11, L25
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1 Introduction

Implementing a sound economic policy is of crucial importance for developing and transition economies. Trade policy is one instrument that a government can use to promote economic development and growth. This paper contributes to the growing body of empirical literature that tries to investigate the linkages between foreign trade and economic outcomes at the plant level. My objective is to provide a better understanding of the impact of access to foreign markets on firm performance in Ukraine. If there is evidence that exporting leads to improved firm performance and consequently better economic outcomes, should the government promote exporting to boost overall productivity?

Earlier theoretical work related to the so-called "new theory" treated all firms within a sector as homogenous. However, growing empirical research at the firm level has shown that firms are very different even within 4-digit sectors. Differences in performance are often driven by whether firms serve only the domestic market or also export their products. Challenged by the empirical evidence on the diversity among firms, a number of theoretical models featuring heterogeneous firms have been developed. Melitz (2003) introduced heterogeneity among the producing agents by assuming that firms differ in their productivity Melitz and Ottaviano (2005) further exploited the possibility of variation among firms by allowing for changing elasticities of substitution between differentiated goods. As summarized by Baldwin (2005), two main features of the heterogeneity models are (1) firms with different marginal costs in same sector and (2) fixed costs of entry to both domestic and foreign markets. The main implications of these models are: (a) exporters should significantly differ from non-exporting firms in terms of productivity; (b) access to a bigger market should lead to an improvement in productivity; and (c) trade liberalization should foster reallocation of market share towards more productive firms.

Existing empirical evidence can be divided into two main streams. The first stream includes studies tracking changes in firms' performance resulting from major trade policy shifts, such as trade liberalization. One of the first attempts to investigate the relationship between industry- and plant-level productivity and trade policy empirically was made by Pavcnik (2002). In this study she used a dataset covering Chilean manufacturing enterprises. As her dataset spanned more than a decade at the time when major Chilean trade reforms were occurring, Pavcnik was able to track changes in productivity associated with trade policy instruments. She found empirical support for the hypothesis that increasing productivity of Chilean manufacturing plants in the import-competing sectors was associated with trade liberalization, while export-oriented sectors did not seem to be affected by this policy change. Peluffo (2004) as well observes only weak evidence of a positive effect of Uruguayan trade liberalization on the industries' productivity; she also shows that technology and market structure seem to be important for explaining differences in performance.

For an extensive survey of micro-level evidence on the link between trade policy and firm productivity in developing countries, see Epifani (2002), who concludes that there is evidence of trade liberalization bringing about productivity gains, especially in import-competing sectors, mainly through resource reallocation towards more productive agents.

The other stream of empirical literature focuses on the causes of superior performance by exporters; that is, whether more productive firms self-select into entering foreign markets or it is exporting that makes those firms that engage in it differ from their counterparts that serve only the domestic market. Bernard and Jensen (1999) inspect the causality link between exporting and firm performance using U.S. manufacturing data. They attempt to determine whether more productive ex ante firms self-select into exporting or whether exporting per se improves firm performance. The study shows that over longer horizons exporting firms do not outperform non-exporters in terms of productivity. However, the TFP numbers they use are estimated residually from the production function with coefficients obtained by simple OLS. As Olley and Pakes (1996) have shown, OLS produces biased estimates of the coefficient on the variable input (labor, in this case); thus, the Bernard and Jensen finding of no superior performance by exporters may, in part, be driven by their estimation technique. Girma et al. (2002) compare exporting and non-exporting U.K. firms by applying matching techniques using TFP, as estimated from OLS regressions with time-specific effects. They find evidence that exporting firms are more productive and that self-selection into exporting occurs. However, contrary to earlier evidence, they find that exporting firms become more productive over time. Arnold and Hussinger (2005) also employ matching for German exporters and non-exporters to show that self-selection is present but that exporting does not further affect productivity. Delgado, Farinas and Ruano (2002) using a Spanish dataset demonstrate higher levels of productivity for exporting firms, finding evidence in support of the self-selection rather than the learning hypothesis. Alvarez and Robertson (2004) make an implicit assumption about the channel, through which exporting influences firms' productivity. They assume that different types of innovation undertaken by Chilean and Mexican plants are indicators of productivity changes and find that exposure to foreign markets is positively associated with technological advancements and innovations. Recently Van Biesebroeck (2005) has approached the issue of self-selection versus learning-by-doing with three different estimation methods yielding robust support to the claim that African firms experience improvements in productivity after entering foreign markets: that is, not only do exporters ex ante differ from their non-exporting counterparts, but also they become more productive within the exporting period.

Summing up, there is convincing evidence that exporting firms, on average, are more productive than their counterparts oriented only to domestic markets. However, whether the exporters' performance improves as a result of sales in foreign markets remains unclear. My research contributes to the latter stream of research.

To estimate plant-level productivity I utilize the methodology developed by Olley and Pakes (1996)[1] in their seminal paper on telecommunication industry

[1] Hereinafter referred to as O-P

in the U.S. This methodology was further used in a number of empirical papers studying the effects of different policy shocks on the industrial dynamics.

The idea behind the O-P methodology is in eliminating two potential biases when estimating production function coefficients. The first type of bias is attributed to simultaneity of the choice of variable inputs. The second bias arising in the estimation of the production function by OLS is caused by selection, due to the pattern of firm exit from the market; firms with greater capital stock will remain in the market thus biasing the coefficient on capital. Olley and Pakes use a multi-stage four-order polynomial expansion to recover the coefficients on labor, capital, and age of firm. I use two specifications of the production function when estimating my model by the O-P methodology – with and without age. In contrast to O-P, who postulate that older enterprises are more productive since they have longer experience in market operations, my prior is that for a country in transition, such as Ukraine, age could actually negatively affect productivity. The reason behind this hypothesis is that the older the plant is, the more outdated the machinery and equipment it uses. Given the credit constraints faced by enterprises in transition economies, plants are often not able to modernize their production process to keep up with the technical progress.

Given the limited nature of my dataset and in order to check the robustness of my TFP estimates, I apply a second approach developed by Levinsohn and Petrin (2003), who use intermediate inputs to proxy for unobserved productivity instead of using investment. Though the coefficients obtained by the two methods differ somewhat, the encouraging result is that the distributions of productivity indices (TFP) for the whole sample look very much the same. Since my main interest is not in estimating precise production function coefficients but in obtaining a consistent estimate of TFP, I ignore these observed differences and continue with the modified O-P methodology.

To my knowledge, there have been very few attempts to investigate exporting and firm performance for countries in transition, and especially, countries of the former Soviet Union. The main reason for such neglect is clearly data unavailability for this set of countries. Obviously, statistics agencies of these countries do collect information and reporting of business entities; however, as in the case of Ukraine, the state statistics committees do not release the data on individual enterprises to the public. Hence, the only possible source of data is various surveys and the reporting of the publicly listed (joint stock) companies. I am not aware of any survey in Ukraine that extensively covers production data, including fixed assets and investment. At the same time, joint stock companies are required by law to report on an annual basis all business-related information, such as balance sheets, production quantities,and other statistics. This enables me to estimate these companies' production functions. Another advantage of this data is that starting in 1999 these companies have to report their exporting/importing activity. Interestingly, the reporting forms also contain questions on the level of perceived competition and on the main competitors faced by the company. The time coverage of the dataset is 2000-2002.

After obtaining estimates of the production function and subsequently TFP, I can investigate the impact of exporting on firm performance. Throughout my analysis I use two normalized measures of TFP. The first is simply a plant's TFP divided by the average productivity in the industry in a given year. The second index, used by Pavcnik (2002), normalizes the above productivity index by taking into account the productivity of a plant with mean output and mean input level in a base year (in my case, it is 2000), that is, subtracting this "average" plant's productivity from the estimated productivity of a given plant in a given year. The advantage of the latter approach is that it is insensitive to measurement units and also possesses the transitivity property. A simple comparison of kernel density estimates shows that the unconditional distribution of both TFP indices for exporters is shifted to the right; that is, without controlling for other factors, exporters, on average, are more productive than non-exporters (average value of the first index is 1.14 for exporters and 0.90 for non-exporters, the respective numbers for the second index are 0.65 and -0.1).

To disentangle the impact of exporting on productivity and to control for other observable characteristics of the firms that could influence the differences in the performance of the two groups, I estimate different specifications with TFP as the dependent variable. Lagged export status as well as percentage change in export volumes seem to be positively correlated with TFP in the current period, even if one-period lag of TFP is included.

The next step I take is to determine whether exporters are different because of self-selection or because of learning-by-doing. Initially, I try to see whether lagged productivity affects the probability of exporting and/or exports as a share of total sales. Lagged TFP does seem to affect probability of exporting as well as export volumes in some specifications even when lagged exports is included; however, the result is not robust to changes in the set of other RHS variables.

Since my dataset's time coverage is not long enough to run any causality tests, I employ two different matching methods. The first is kernel matching solely on propensity score, while the second is a combination of matching on propensity score and Mahalanobis metric matching within specified caliper. Matching allows a comparison of outcomes of interest of the treated group with control group based on some observable characteristics that influence the probability of being treated (exporting, in my case) (Heckman et al. 1998). The simple kernel matching estimator uses information on the entire set of controls assigning a smaller weight to the observations that are farther away in terms of propensity score from a given treated observation. The second method matches observations not only on the propensity score but also on a set of key covariates using the Mahalanobis distance. As Rubin and Thomas (2000) show, combining the two methods helps to reduce most of the balancing bias.

Both methods show that the difference between exporters and non-exporters does not disappear once self-selection is controlled for. However, since with matching I am able to control only for the observable determinants of exporting, there might be some important unobservable differences that drive this result. This leaves the door open for further investigation.

2 Theoretical background

Earlier theoretical work related to the so-called "new theory" treated all firms within a sector as homogenous. However, growing empirical research at the firm level has shown that firms seem to be different in terms of productivity even within 4-digit sectors. Differences in performance are often explained by whether firms serve only the domestic market or also export their products. Challenged by the empirical evidence on the diversity among firms, a number of theoretical models featuring heterogeneous firms have been developed. Melitz (2003) introduces heterogeneity among the producing agents by assuming that firms differ by their productivity, which is drawn randomly from a given distribution. Prior to the revelation of their productivity, firms have to incur fixed costs of entry. Once the productivity draws are realized, firms make a decision on whether to stay in the market given the estimated present value of the profit stream. Since all the firms face the same fixed costs of entry (incurred prior to the realization of the productivity draw), only firms above a certain productivity threshold will stay in the market. The Melitz model allows us to study the implications of trade policy on firm performance. In this model, if there are no trade costs, trade is equivalent to an increase in the size of the closed economy, which does not affect firm-level outcomes. However, if entry into a foreign market is associated with some fixed costs as well, only the most productive firms will serve both the domestic and foreign markets. Trade liberalization will affect aggregate productivity by forcing the least productive firms out of the market and shifting market shares towards more productive firms (reallocation effect).

Melitz and Ottaviano (2005) further exploited the possibility of diversity among firms by allowing for changing elasticities of substitution between differentiated goods. In contrast to the Melitz model, here market size does have an effect on firm-level outcomes. As a result, the model allows for a pro-competitive effect of trade liberalization, which manifests itself in falling prices (in addition to the reallocation effect present in the Melitz model). According to the Melitz and Ottaviano model, productivity will affect the size of the firm, the prices it charges as well as mark-ups, with more productive firms being larger, charging lower prices, and having bigger mark-ups. Hence, in this model, the direction of causality is from productivity to size and not from size to productivity as would be implied by, for example, the effect of increasing returns to scale. Empirical literature routinely uses firm size variables as controls in determining the relationship between firm characteristics and firm performance (see, for example, Castany et al. 2005). In this paper I am also trying to investigate the link between size and productivity, and the results I obtain provide support to the implications of the Melitz and Ottaviano model.

Bernard et al. (2003) use a modified version of the Ricardian model of stochastic comparative advantage to explain the interconnection between exporting, size, and productivity. They assume the existence of "iceberg" costs of exporting, which allow only more productive firms (those with the least marginal costs) to sell to other countries. Thus, this model provides an explanation to the well-documented phenomenon of the presence of both exporting and non-exporting firms in the same 4-digit industry.

In another model, Bernard et al. (forthcoming) follow Melitz (2003) by combining monopolistic competition and unit costs that depend on firm productivity. In addition to heterogeneity among firms, industries are characterized by different factor intensities, while relative abundance of factors of production varies across countries. This model manages to capture both macroeconomic and microeconomic aspects of international trade: (1) relative export intensity of different industries in different countries; (2) existence of intra-industry trade; and (3) coexistence of exporting and non-exporting firms within the same industry.

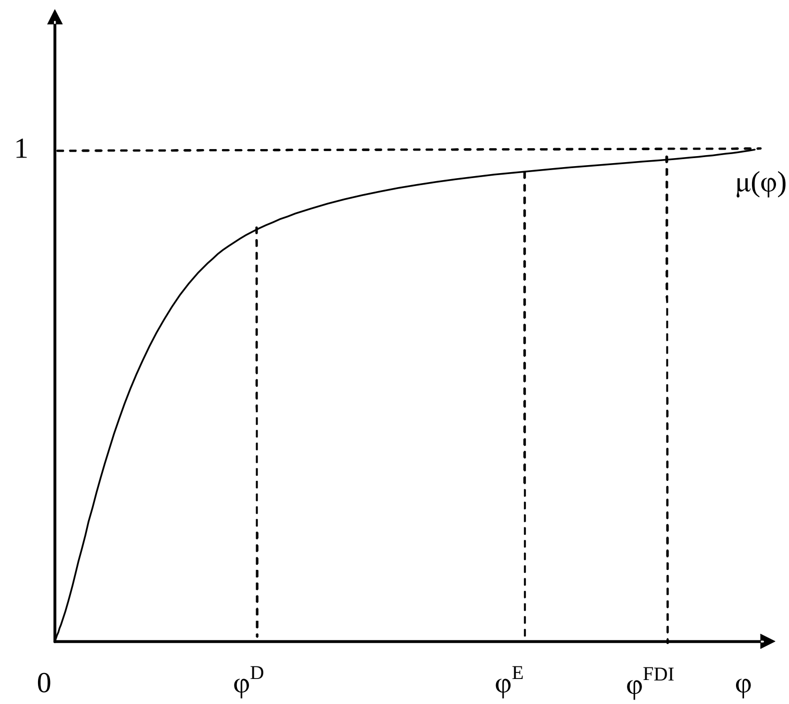
Helpman et al. (2004) study the effect of heterogeneity among firms on their decision whether to export or set up a subsidiary (FDI). Since the former is associated with lower fixed costs, only most productive will use FDI to serve foreign market. Schematic representation of the models is presented in Figure 1 where the Pareto distribution of productivity[2] with various cutoff points is plotted. Firms to the left of the cutoff point φ^D will not produce, firms in the interval between φ^D and φ^E will serve only the domestic market, while firms to the right of φ^E will export. As discussed above, Helpman et al. show that outward-oriented firms will be further partitioned into exporting firms and firms engaged in FDI (the far-right cutoff point φ^{FDI}).

In a model developed by Yeaple (2005), firms are identical ex ante and become heterogeneous because they choose to use different technologies and different types of workers. The model implies that exporting firms are those that employ superior technology with lower unit costs and higher-skilled workers.

As summarized by Baldwin (2005), two main features of the heterogeneity models are (1) firms with different marginal costs in the same sector and (2) sunk costs of entry to both domestic and foreign markets. The main implications of these models are: (a) exporters should significantly differ from non-exporting firms in terms of productivity; (b) access to a bigger market should lead to an improvement in productivity; and (c) trade liberalization should foster reallocation of market share towards more productive firms.

[2]Without loss of generality, Melitz and Ottaviano assume the Pareto distribution of the marginal costs (which is the inverse of producitivity in the Melitz model).

Figure 1. Productivity distribution and cutoffs for exporting and FDI



3 Data and Methodology

The dataset that I use for estimation was assembled by me from the publicly available annual reports of Ukrainian open joint stock companies. The advantage of this dataset is that it covers a substantial amount of firm-related information, including ownership, output, stock of capital, credit position, among other indicators. The dataset covers a relatively short period, 2000-2002, mainly due to the lack of information on exporting and investment prior to 2000. The period covered by the dataset was characterized by growth in the volume of manufacturing output, exports and real GDP, with exports contributing a significant share of the GDP growth (Figure A1).

The dataset is an unbalanced panel of 1,581 manufacturing enterprises excluding those in the food-processing industry. In total, there are 4,435 observations for the three years, with 95 per cent of the observations reflecting firms that were in operation at the time. The advantages of the dataset are that it has extensive regional coverage: information is available for firms representing all 25 oblasts (regions) and two cities, Kiev and Sevastopol, which are administratively equated to regions; it also follows the structure of manufacturing in the Ukrainian economy. Descriptive statistics for the sample can be found in the Appendix (Section A1). Although machinery has the highest number of firms, it comes only second if one were to look at the sectoral output share in total manufacturing. It should be noted that around 15 per cent of the observations have zero investment and thus, as discussed below, were not used for estimation of the production function coefficients. The majority of the enterprises are relatively large and old, since joint stock companies were created on the basis of the existing enterprises previously owned by the state. Given the above and the fact that firm size is positively associated with exporting, exporters are over-represented in this sample and constitute around 40 per cent of all firms with average shipments abroad around 14 per cent of total sales. Export volumes to the former Soviet Union (FSU) countries are, on average, higher than exports to other countries; however, I should note that there is a gradual shift in the export orientation of Ukraine towards the latter, which is also documented at the macroeconomic level (WB 2005). Twenty-four per cent of the firms imported raw materials in the period under consideration.

The highest share of exporters is observed in metallurgy– around 2/3 of all firms in this sector exported at least some of their output. In aggregate, this sector contributed 44.5, 41.4, and 39.7 per cent to the total volume of the country's exports in 2000, 2001, and 2002, respectively (WB 2005). Around 80 percent of the exporters in metallurgy (check that this is what you meant!) shipped to countries outside of the FSU. This indicator is even higher for textiles, where many plants work on a give-and-take basis, producing clothes and footwear for foreign companies. As expected, producers of construction materials are less likely to export their products (less than 15 per cent of all producing plants export). Exporting activity seems to be very persistent: lagged export status is crucial in predicting exporting in the current period: the correlation coefficient is close to 0.8. High persistency of exporting is often taken as evidence of sunk costs of serving foreign markets.

A first look at the data suggests that exporter status seems to be associated with better indicators of firm performance. Simple OLS regressions of the main performance variables in per worker terms on the export dummy are presented in the Table A3. Exporting firms seem to be bigger in terms of both number of employees and production volume; they also invest more and pay, on average, higher wages.

To estimate plant-level productivity I utilize the methodology developed by Olley and Pakes (1996) in their seminal paper on telecommunication industry in the U.S. This methodology was further used in a number of empirical papers studying the effects of different policy shocks on the industrial dynamics. I use two specifications of the production function when estimating by the O-P methodology – with and without firm age, although in this paper I only report the results of the model without age.[3] In contrast to Olley and Pakes, who postulate that older enterprises are more productive since they have longer experience in market operations, my prior is that for a country in transition, such as Ukraine, age could actually negatively affect productivity. The reason

[3] The reason for reporting only one set of estimates is that I would like further to explore how age of an enterpise may affect its exporting status from the political economics point of view.

behind this hypothesis is that the older the plant is, the more outdated the machinery and equipment it uses. Given the credit constraints faced by the enterprises in transition economies, plants are often unable to modernize their production processes to keep up with the technical progress.

The idea behind the O-P methodology is in eliminating two potential biases when estimating production function coefficients. The first type of bias is attributed to simultaneity of the choice variable inputs. Assuming a Cobb-Douglas production function and representing it in logarithmic form:

$y_{it} = \beta_0 + \beta_a a_{it} + \beta_k k_{it} + \beta_l l_{it} + \varsigma_{it}$

where

$\varsigma_{it} = \omega_{it} + \varepsilon_{it}$

that is, it consists of two parts: ω_{it} is productivity observed by the firm, and ε_{it} is a shock to productivity not observed by the firm. Thus, productivity observed by firms and unobserved by econometricians will influence the firms' choice of the variable input (labor) causing the OLS coefficients on labor to be biased upwards. The second bias arising in the estimation by OLS is the selection bias, which is due to firms' exiting from the market. Olley and Pakes use multi-stage polynomial approximation to recover the coefficients on labor and capital as well as firm age. A detailed description of their methodology can be found in Section A2 in the Appendix. Since one of the O-P assumptions is that investment is an increasing function of unobserved productivity, I use only observations with non-zero investment when estimating the production function.

Upon obtaining the coefficients on inputs I can estimate total factor productivity. To make a meaningful comparison I use two types of productivity indices. The first index is obtained by dividing the TFP of a given plant by the industry average in a particular year.

$$\begin{aligned} TFP &= y_{it} - \widehat{y}_{it} = y_{it} - \widehat{\beta}_l l_{it} - \widehat{\beta}_k k_{it} - (\widehat{\beta}_a a_{it}) \\ \text{Prodindex 1} &= \frac{y_{it}}{\overline{y}_{jt}} \end{aligned}$$

The second index, used by Pavcnik (2002), normalizes the productivity index by taking into account the productivity of the plant with mean output and mean input level in a base year (in my case, it is 2000), that is, subtracting it from the estimated productivity of a given plant in a given year.

$$\begin{aligned} \widehat{y}_{it} &= \widehat{\beta}_l l_{it} + \widehat{\beta}_k k_{it} + (\widehat{\beta}_a a_{it}) \\ y_r &= \overline{y}_{i,base} \\ \widehat{y}_r &= \widehat{\beta}_l \bar{l}_{i,base} + \widehat{\beta}_k \overline{k}_{i,base} + (\widehat{\beta}_a \overline{a}_{i,base}) \\ \text{Prodindex 2} &= y_{it} - \widehat{y}_{it} - (y_r - \widehat{y}_r) \end{aligned}$$

The advantage of the latter is that it is insensitive to measurement units and also possesses the transitivity property.

As a robustness check I re-estimate input coefficients using the Levinsohn and Petrin (L-P) approach as well as a recently developed approach that takes into account the fact that exporters and non-exporters potentially face different market structures. Both methods follow closely the O-P methodology: the L-P methodology specifies using intermediate inputs to proxy for productivity instead of investment. Their approach is especially useful for datasets that have numerous observations with zero investment. Although problem the problem of zero-investment entries is not particularly pressing in my case, but taking into account a short time span and also limited number of observations in my dataset, I use this approach to re-estimate the coefficients of the production function by sub-industries in order to check the robustness of the estimates. The second approach modifies the O-P methodology by adding export status variables to the first two estimation stages. In their original paper, Olley and Pakes estimate production function coefficients for the U.S. telecommunication industry. Since this industry could be treated as a non-tradable sector, they did not make any assumptions on how exporting versus non-exporting could influence the firms' investment decisions or exit decisions. Several authors investigating the export-productivity link have attempted to solve this problem explicitly by controlling for export status within the O-P methodology. For example, Van Biesebroeck (2005) uses lagged export status as a state variable in the investment decision and exit decision. De Loecker (2005) introduces current export status in the investment and exit decision. Since I am using De Loecker's methodology I describe it in greater detail in Section A2 of the Appendix and hereinafter will refer to this methodology as D-L or export-augmented O-P, interchangeably.

The next step is to determine whether performance of exporters is different from that of non-exporters because of self-selection or because of learning-by-doing. Since my dataset's time coverage is not long enough to run any causality tests I employ two different matching methods. The first is kernel matching solely on propensity score, while the second is a combination of matching on propensity score and Mahalanobis metric matching within a specified caliper. Matching allows a comparison of outcomes of interest between the treated group and the control group, based on some observable characteristics that influence the probability of being treated (exporting, in my case) (Heckman et al. 1998). The kernel matching estimator uses information on the entire set of controls assigning a smaller weight to the observations lying farther away in terms of propensity score from a given treated observation. The second method matches observations not only on the propensity score but also on a set of key covariates using the Mahalanobis distance. As Rubin and Thomas (2000) show, combining the two methods helps to reduce most of the balancing bias.

When applying a matching technique, I face a trade-off of satisfying the balancing property or capturing the maximum of firms' characteristics that are related to the firms' probability of becoming exporters. Following Girma et al. (2002), I am estimating the following probit model, where the dependent variable is the export dummy, controlling for year and industry effects:

$$\Pr(Export = 1) = f(TFP_{t-1}, \mathrm{Si}\,ze_{t-1}, Wage_{t-1}, Ownership_{t-1})$$

My model is more parsimonious than the one used in other studies; for example, I do not include lagged export status as a predictor for exporting. Given that exporting seems to be a highly persistent activity and the absence of significant entry in and exit from the foreign market in my dataset, inclusion of lagged export will never allow the satisfaction of the balancing property (i.e. for the mean of variables describing firm characteristics to equal for two groups within a block) since the distributions of the propensity scores for exporting and non-exporting groups will be lying very far apart.

Matching has been already applied in similar studies of other countries' data. Arnold and Hussinger (2005) use one-to-one nearest neighbor method to match exporting and non-exporting firms. In their specification of the probit model of selection into exporting they use a lagged export dummy and a set of firm characteristics. They report that the difference between propensity scores for matched pairs lies in a very narrow range. De Loecker (2005), taking advantage of the Slovenian data, which exhibit a high degree of shifting in and out of the foreign market activity, looks only at firms that started to export over the period. In particular, he estimates propensity scores using the following model:

$$\Pr\{Start_{i,0} = 1\} = \phi\{h(\omega_{i,-1}, k_{i,-1}, \mathrm{Private}_{i,-1})\}$$

where $h(\cdot)$ is a full polynomial of the three variables. He finds that firms which start to export experience a productivity improvement both in terms of levels and growth rates. His approach is definitely less sensitive to this trade-off between satisfying balancing property and using bigger set of observables to build propensity score as lagged export status does not enter into probit specification.

4 Results

4.1 Input coefficients and TFP

I estimate production functions separately for each 2-digit industry. Given the fact that production function implies that it is real output which is produced with inputs, before starting any estimation I deflate all nominal values using 2-digit industry-specific producer price indices. As discussed in the literature (see, for example, Pavcnik 2002), the right approach would be to use firm-level prices to convert nominal output into real. Deflation using industry-specific indices may attribute a higher level of productivity to the plants that simply charge higher mark-ups and are not necessarily more productive. However, according to the Melitz-Ottaviano model, more productive firms (lower-cost firms in the model) will be the ones to charge higher mark-ups. Hence, the resulting productivity estimates may be biased only if the above result of the Melitz-Ottaviano model is not true.

Table A4 presents labor and capital coefficients estimated using the following methodologies: OLS, original Olley and Pakes, export-augmented Olley and Pakes, as well as Levinsohn and Petrin methodology. As expected, the OLS coefficients on variable input (labor) are much higher, confirming the presence of an upward bias caused by simultaneity. The Olley and Pakes procedure eliminates this bias, producing lower coefficients on labor. Most of the coefficients on capital are not statistically significant at the conventional levels. One possible explanation is that all three nonparametric procedures use nonlinear minimization at the last stage of estimation to recover coefficients on capital; given the limited number of observations, this may lead to bigger standard errors.

I proceed by estimating the two productivity indices as defined in section 3. Table A5 shows the resulting productivity indices calculated from estimates of the input coefficients obtained by the three nonparametric methods discussed above. Even at first glance, the average values of both types of indices allow me to conjecture that all three methods produce very similar estimates of total factor productivity. Further examination of the kernel density plots of TFP distributions across different methods confirms the above hypothesis: indeed, the distributions look very much the same (Figures A2-A3). I consider this as confirmation of the robustness of my TFP estimates. Since it is productivity and not coefficients per se that is the focal point of my research, I will use only one set of indices estimated with the export-augmented Olley and Pakes approach, since it is methodologically more consistent and allows me to control for different market structures for exporting and non-exporting firms.

4.2 Productivity and Exporting

As I am interested in the relative performance of exporting and non-exporting firms I look at the first two moments of the TFP distributions for the two groups. Table A6 compares TFP indices for exporting and non-exporting groups across industries. For all industries exporting firms are, on average, doing better in terms of productivity. Moreover, productivity distribution for non-exporters appears to be more dispersed, except for the chemicals industry. Differences between the two groups are further confirmed by the kernel density plots[4] estimated by the three nonparametric methods (Figures A4-A6), showing unconditional distribution of total factor productivity for the two groups, where the distribution of the exporting group is shifted to the right.

To disentangle the impact of exporting and control for other observable firm characteristics that could affect the differences in the performance of the two groups, I estimate different specifications with TFP indices as the dependent variables. The results are presented in Table A7. Lagged export status as well as exports as per cent of total sales and change in exporting status seem to be positively correlated with TFP in the current period, even when a one-period lag of TFP is included. The effect seems to be robust to the inclusion of other

[4]Kernel density plots are for productivity index 1. The picture is similar for the second index as well.

controls, such as location, size, and ownership. As found by other studies (see e.g. Arnold and Smarzynska Javorcik 2005) increase in the foreign-owned share is positively associated with the improvement in the total factor productivity. Previous studies linking ownership and firms performance in Ukraine also demonstrate that management-owned firms are doing better than firms with other ownership structure.

When I repeat the same exercise now putting export variables on the LHS and regressing lagged productivity indices on a set of controls, I also find that lagged TFP seems to be important in affecting export volumes, when lagged export and other control variables are included. This simple exercise does not allow me to determine the causality between exporting and productivity. Higher share of foreign ownership seems to increase both probability of exporting and level of exports.

As discussed in Section 3, several studies (Arnold and Hussinger 2005; Girma et al. 2002, De Loecker 2005) have applied matching based on propensity score to uncover the underlying relationship between exporting and firm performance, but they delivered mixed evidence on whether exporting leads to better performance.

The results of the two matching methods for both indices are presented in Tables A7-A8. Both methods deliver the same results of the persistence of the TFP differential between the two groups after controlling for self-selection. For both matching methods, the results when using an index constructed with reference to a base year show that the difference in performance between exporting and non-exporting firms remains. However, when using the productivity index normalized by the industry average as an outcome of the treatment, the difference between exporters and non-exporters does not seem to be robust when two matching methods are applied. As discussed in section 3, I use the more parsimonious probit model for estimation of the propensity score. I am rather cautious in interpreting my results, since I might be attributing differences in productivity to exporting when they are indeed caused by other observed or unobserved firm characteristics.

4.3 Productivity and Size

As discussed in Section 2, one of the implications of the Melitz and Ottaviano model is that it is productivity that drives the differences in the size of firms within an industry. To investigate this link I construct a simple cross-section regression.

$$\Delta \mathrm{Si}\,ze_t = f(\Delta TFP_{t-1}, TFP_{t-2}, Z)$$

$$\Delta TFP_t = f(\Delta \mathrm{Si}\,ze_{t-1}, \mathrm{Si}\,ze_{t-2}, Z)$$

where Z is a vector of control variables and $\Delta X_{t-1} = X_{t-2} - X_{t-1}$ and $\Delta X_t = X_{t-1} - X_t$

The results of the estimation are presented in Table A12. Both the two-period lagged productivity (productivity in 2000) and the change in productivity (from 2000 to 2001) seem to be positively associated with the increase in size measured as a log of the number of employees (from 2001 to 2002). At the same time, the lagged change in size does not seem to affect the change in productivity. The negative coefficient on the two-period lagged size suggests that relatively smaller firms in 2000 saw a bigger improvement in productivity from 2001 to 2002.

Productivity affects both size and exporting status. All the previous studies have found exporters to be significantly larger than non-exporting firms. Given the results in the previous subsection, I can hypothesize the direction of the links between exporting, size, and productivity. As more productive firms become larger, they are more likely to export if exporting is associated with some fixed costs. Obviously to make a stronger conclusion on the direction of causality one would need a longer panel to see whether this pattern holds. Another approach would be to investigate this issue using firm-level data from other countries.

5 Concluding remarks

In this paper, I examined the empirical implications of the new theoretical models with heterogeneous firms regarding interlinkages between productivity, exporting, and size. As previous studies have shown, exporters are different from non-exporters. Many studies have found that it is self-selection of firms that drives this difference; that is, exporters ex ante are different from domestic counterparts. To estimate productivity I employed the semi-parametric procedure developed by Olley and Pakes, which delivers consistent estimates of TFP. As my results showed, Ukrainian exporters indeed seem to be more productive than Ukrainian non-exporters. This difference remained when I controlled for observable characteristics of the plants using matching techniques. However, I used a more parsimonious probit model for estimation of the propensity score. I treat this result with caution since I might be attributing differences in productivity to exporting when they are actually caused by other observed or unobserved firm characteristics.

Productivity appears to affect both size and exporting status. All the previous studies have found exporters to be significantly larger than non-exporting firms. The results that I obtained seem to suggest that as more productive firms become larger, they are more likely to export if exporting is associated with some fixed costs. Obviously to make a stronger conclusion on the direction of causality one would need a longer panel to see whether this pattern holds. Another approach would be to investigate this issue using firm-level data from other countries.

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6 Appendix

6.1 Section A1. Data description

Figure A1. Export dynamics and Real GDP growth.

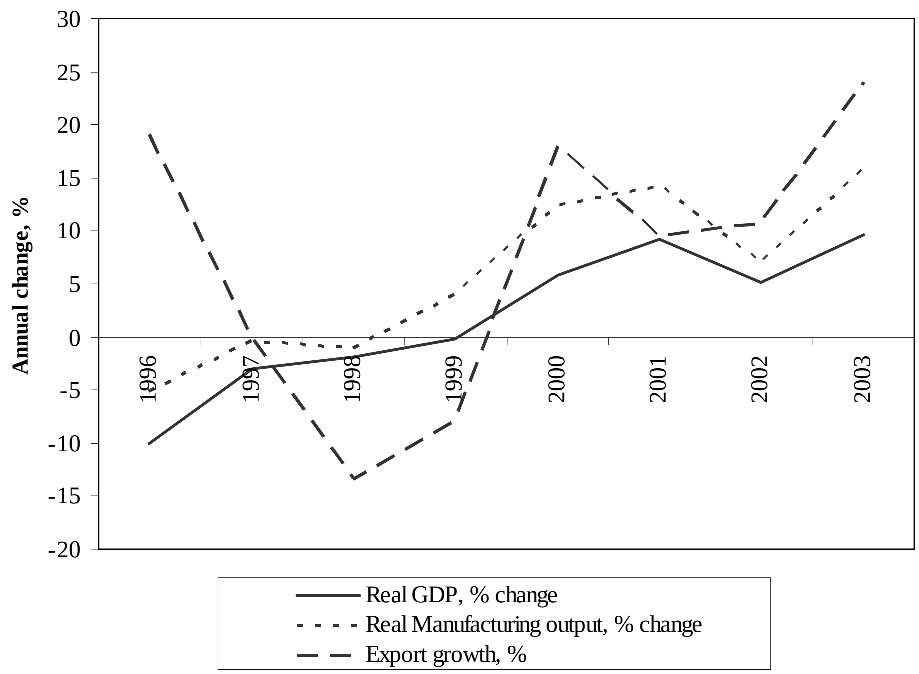

Table A1. Industrial division

Industry	Obs	Ind sales as %, data set	Ind sales as %, economy[5]
Metals	300	63.24	46.5
Chemicals	303	8.76	14.5
Machinery	2223	20.44	24.8
Paper and wood	462	2.57	4.7
Construction materials	924	3.71	6.5
Textiles and footwear	531	1.28	3.0
Total	4743	100	100

Table A2. Descriptive statistics

Variable	Mean	STD	Obs
Age	49.8	30.2	4228
Employees	778	2810	4228
Output	36527.0	238605.0	4228
Net sales	36938.9	232946.6	4228
Value added	11255.9	80327.6	4228
Investment	1226.9	8578.6	4228
Machinery and equipment	6581.1	33330.5	4228

Table A3. Export status and main indicators of firms' performance.[6]

Variable	Mean	St. Er	Obs
Output	0.459	(0.040)**	4226
Net Sales	0.458	(0.038)**	4224
Value added	0.43	(0.044)**	3788
Machinery and equipment	0.129	(0.042)**	4192
Investment	0.569	(0.085)**	2330
Average wage	0.253	(0.022)**	4226

[5] For comparison manufacturing total sales are calculated excluding food-processing and resource-extracting and gas-, water- power-generating industries

[6] All variables are per worker. Average wage is calcualted as firm's payroll fund divided by number of employees.

6.2 Section A2. Olley and Pakes (1996) methodology[7]

O-P assumes the Cobb-Douglas production function expressed in logs:

$$y_{it} = \beta_0 + \beta_a a_{it} + \beta_k k_{it} + \beta_l l_{it} + \varsigma_{it} \tag{1}$$

where, in turn, error term consists of two parts: productivity observed by the firm ω_{it}, which follows Markov process over time and random shock to productivity ε_{it}.

$$\varsigma_{it} = \omega_{it} + \varepsilon_{it} \tag{2}$$

Firms maximize their discounted profits given their perceptions about the future evolution of the market structure. At time t, a firm makes two decisions: (1) whether to produce or exit and (2) how much to invest. In particular, firms with productivity level below some threshold will exit from the market. The exit rule then:

$$X_t = \begin{cases} 1 & \text{if } \omega_t \geq \underline{\omega}_t(a_t, k_t) \\ 0 & \text{otherwise} \end{cases}$$

Investment decision will depend on the observed productivity, current stock of capital and also the experience (age) of the firm. Hence, investment at time t can be formalized as follows:

$$i_t = i_t(\omega_t, a_t, k_t) \tag{3}$$

Further, Olley and Pakes make assumption of productivity strictly increasing in investment, which allows to express unobservable ω_t as a function of investment, capital and age.

$$\omega_t = h_t(i_t, a_t, k_t) \tag{4}$$

Simple estimation of the production function using OLS will produce two types of biases: (1) endogeneity (simultaneity) biases arises since firms choose inputs conditional on their perceptions about ω_t, as a result coefficients on variable inputs will be biased upward. Second type of bias is caused by firms exiting decisions. The threshold productivity is decreasing in capital and hence firms which have larger capital stock will stay in the market at lower level of ω_t. This will produce downward bias in the capital coefficient.

To resolve these two problems O-P suggested alternative to OLS estimation procedure, which they prove to deliver consistently estimated coefficients on the inputs.

At the first stage, consistent estimate of the labor coefficient is obtained by estimating the following specification:

$$\begin{aligned} y_{it} &= \beta_l l_{it} + \phi_t(i_t, a_t, k_t) + \varepsilon_{it} \quad \text{where} && (5) \\ \phi_t(i_t, a_t, k_t) &= \beta_0 + \beta_a a_{it} + \beta_k k_{it} + h_t(i_t, a_t, k_t) && (6) \end{aligned}$$

[7] This section draws extensively on the Olley and Pakes (1996) and simply presents their methodological procedure. For greater detail, please, refer to the original paper.

Function $\phi_t(i_t, a_t, k_t)$ is approximated with 3rd or 4th order polynomial series in triple i_t, a_t, k_t.

In order to consistently estimate coefficients on capital and age, O-P first estimate probability of staying in the market at time $t+1$ conditional on perception of the productivity realization which in turn depend on the available capital stock and age of the firm at time t. Formally,

$$\begin{aligned}
\Pr(X_{t+1} &= 1|\underline{\omega}_{t+1}(a_{t+1}, k_{t+1}), J_t) = \\
&= Pr(\omega_{t+1} \geq \underline{\omega}_{t+1}(a_{t+1}, k_{t+1})|\underline{\omega}_{t+1}(a_{t+1}, k_{t+1}), \omega_t) \\
&= \psi_t(\underline{\omega}_{t+1}(a_{t+1}, k_{t+1}), \omega_t) \\
\Pr(X_{t+1} &= 1|\underline{\omega}_{t+1}(a_{t+1}, k_{t+1}), J_t) = \psi_t(i_t, a_t, k_t) = P_t \qquad (7)
\end{aligned}$$

At the final stage, the coefficients on age and capital are retrieved by estimating the following equation using h non-linear algorithm since coefficients on age and capital enter in non-linear way:

$$y_{t+1} - \beta_l l_{t+1} = \alpha + \beta_a a_{t+1} + \beta_k k_{t+1} + \sum_{j=0}^{4-m} \sum_{m=0}^{4} \beta_{mj} \widehat{h}_t^m \widehat{P}_t^J + e_{t+1} \qquad (8)$$

where $\widehat{h}_t = \widehat{\phi}_t - \beta_a a_t - \beta_k k_t$

This step concludes O-P algorithm.

De Loecker (2005) modification

De Loecker drops age as a state variable and introduces export status dummy into investment function

$$i_t = i_t(\omega_t, e_t, k_t) \qquad (9)$$

Similarly to O-P he continues to assume that productivity follows Markov process. However, now export status also affects survival probability of the firm: as exporting firms are on average more capital abundant and they will be more prone to stay in the market even at lower realizations of productivity. To control for this, De Loecker includes export dummy into second-stage estimation of survival probability:

$$\Pr(X_{t+1} = 1|\underline{\omega}_{t+1}(e_{t+1}, k_{t+1}), J_t) = \psi_t(i_t, e_t, k_t) = \widetilde{P}_t \qquad (10)$$

The final stage equation includes export-adjusted probability of survival:

$$y_{t+1} - \beta_l l_{t+1} = \alpha + \beta_k k_{t+1} + \sum_{j=0}^{4-m} \sum_{m=0}^{4} \beta_{mj} \widehat{\widetilde{h}}_t^m \widehat{\widetilde{P}}_t^J + e_{t+1} \qquad (11)$$

where $\widehat{\widetilde{h}}_t = \widehat{\widetilde{\phi}}_t - \beta_k k_t$

and where $\widehat{\widetilde{\phi}}_t$ is estimated as predicted value from $\phi_t(i_t, e_t, k_t) = \beta_0 + \beta_k k_t + h_t(i_t, e_t, k_t)$

6.3 Section A3. Results

Table A4. Input coefficients

	OLS		O-P		O-P with export		L-P	
	Labor	Capital	Labor	Capital	Labor	Capital	Labor	Capital
Metals	0.781	0.268	0.619	0.48	0.597	0.444	0.308	0.267
	-0.093	-0.077	-0.122	-0.094	-0.128	-0.078	-0.112	-0.219
Chemicals	0.936	0.213	0.582	-0.088	0.34	-0.225	0.063	0.008
	-0.095	-0.075	-0.13	-0.059	-0.136	-0.152	-0.119	-0.117
Machinery	1.059	-0.006	0.718	0.138	0.702	0.069	0.376	0.115
	-0.032	-0.025	-0.045	-0.034	-0.046	-0.063	-0.061	-0.098
Paper and wood	0.822	0.295	0.588	-0.115	0.606	-0.148	0.257	0.036
	-0.092	-0.067	-0.137	-0.113	-0.139	-0.145	-0.111	-0.191
Construction materials	1.07	0.193	0.652	0.056	0.633	0.223	0.262	0.288
	-0.055	-0.038	-0.082	-0.049	-0.083	-0.064	-0.077	-0.12
Textiles and footwear	0.727	0.249	0.537	-0.149	0.477	-0.074	0.483	0.236
	-0.065	-0.048	-0.097	-0.087	-0.104	-0.098	-0.11	-0.096

Table A5. Comparison of TFP indices across methods.

	Exporters	**Non-exporters**
Prodindex1 (O-P)	1.141	0.903
Prodindex1 (O-P with exports)	1.138	0.906
Prodindex1 (L-P)	1.149	0.898
Prodindex2 (O-P)	0.654	-0.096
Prodindex2 (O-P with exports)	0.684	-0.118
Prodindex2 (L-P)	0.799	-0.257

Table A6. Comparison of TFP indices by industries.

Prodindex 1	Exporters		Non-exporters	
	Mean	STD	Mean	STD
Metals	1.030	0.654	0.932	0.753
Chemicals	1.188	0.258	0.831	0.214
Machinery	1.126	0.434	0.889	0.459
Paper and wood	1.321	0.389	0.918	0.373
Construction materials	1.248	0.460	0.957	0.608
Textiles and footwear	1.137	0.241	0.852	0.323
Total	1.138	0.439	0.906	0.489

Prodindex 2	Exporters		Non-exporters	
	Mean	STD	Mean	STD
Metals	0.147	0.917	0.028	1.089
Chemicals	1.540	1.830	-0.984	1.553
Machinery	0.570	1.141	-0.061	1.206
Paper and wood	1.357	1.546	-0.275	1.516
Construction materials	0.732	0.924	0.125	1.231
Textiles and footwear	0.884	1.085	-0.401	1.457
Total	0.684	1.233	-0.118	1.322

Figure A2. Kernel density of TFP index1 estimated by O-P and modified O-P.

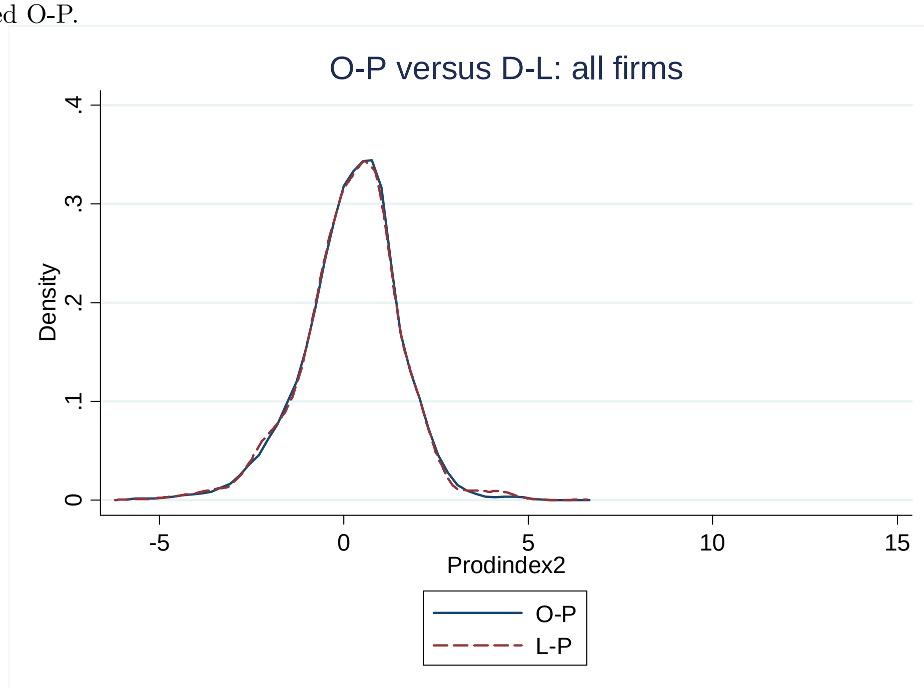

Figure A3. Kernel density of TFP index1 estimated by O-P and L-P.

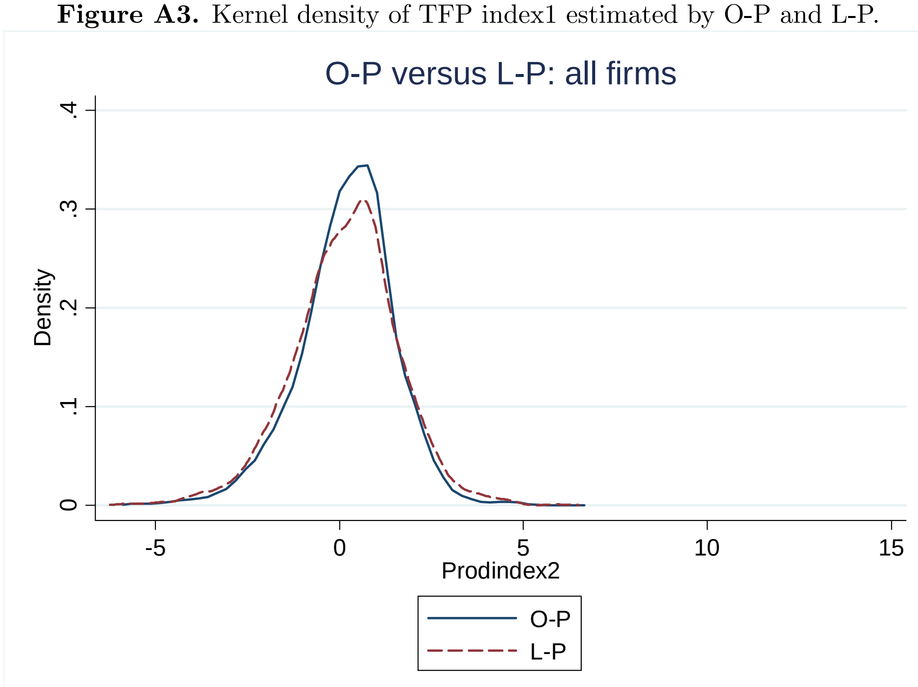

Figure A4. Kernel density of TFP index1 estimated by O-P and L-P.

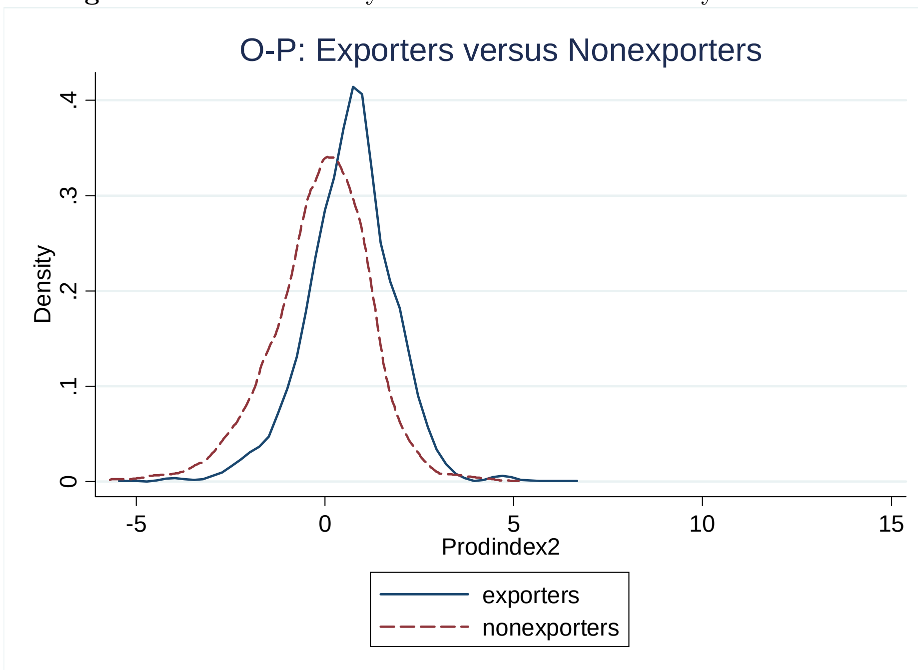

Figure A5. Kernel density of TFP index1 estimated by O-P and L-P.

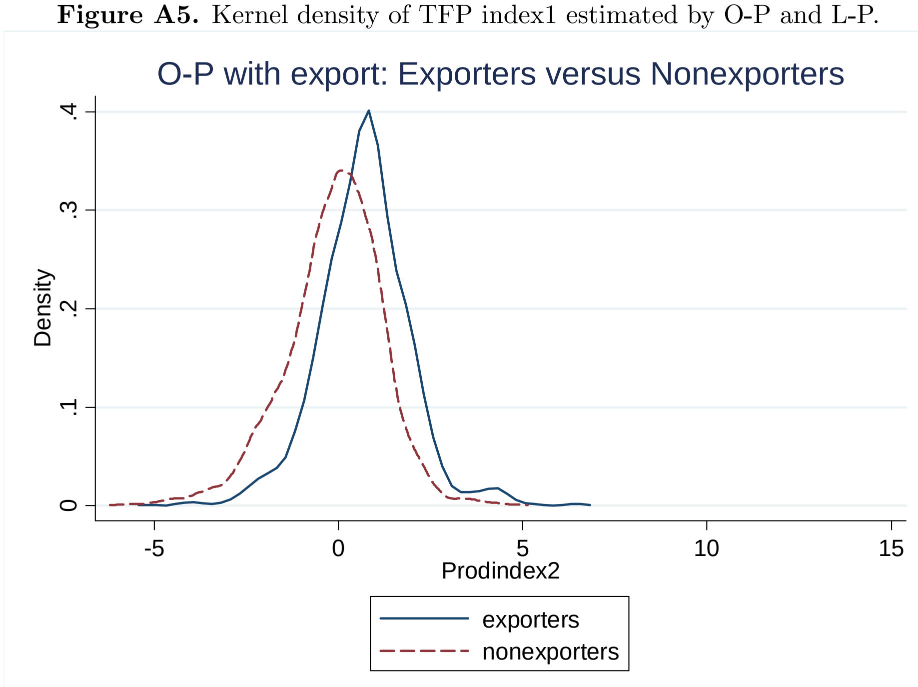

Figure A6. Kernel density of TFP index1 estimated by O-P and L-P.

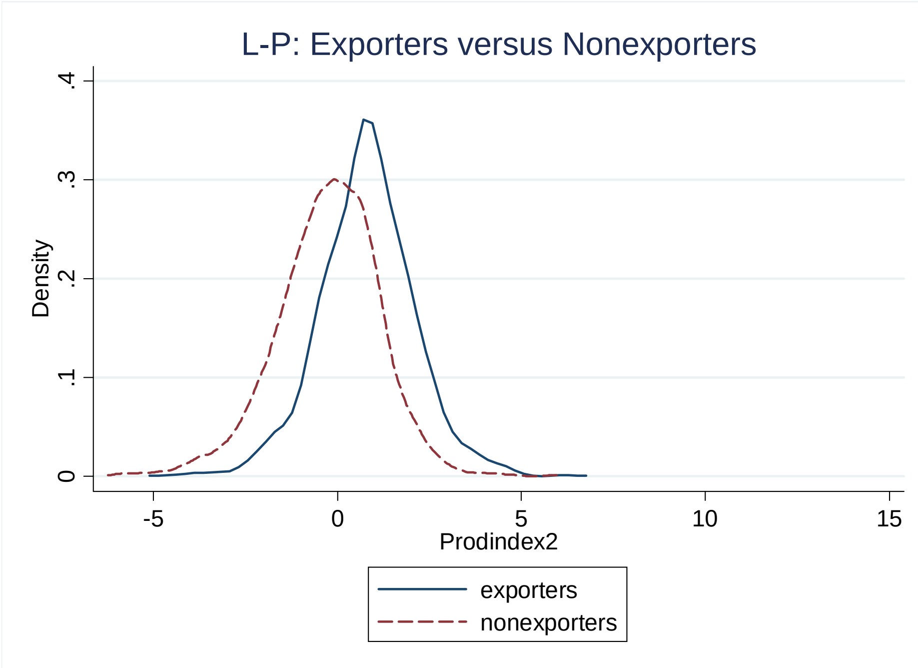

Table A7. Chicken or egg: Lagged exports and current TFP[8]

	TFP1	TFP2	TFP1	TFP2	TFP1	TFP2
Lagged export status	0.077	0.203				
	(0.017)**	(0.045)**				
Change in export,						
(%t-%(t-1))			0.001	0.005	0.001	0.004
			(0.000)**	(0.001)**	(0.000)**	(0.001)**
Lagged TFP1/ TFP2	0.526	0.618	0.545	0.640	0.484	0.571
	(0.022)**	(0.022)**	(0.021)**	(0.021)**	(0.023)**	(0.023)**
Age	0.000	0.001	0.001	0.002	0.000	0.000
	(0.000)	(0.001)*	(0.000)*	(0.001)**	(0.000)	(0.001)
Foreign share	0.002	0.005	0.002	0.005	0.001	0.004
	(0.000)**	(0.001)**	(0.000)**	(0.001)**	(0.000)**	(0.001)**
State-owned share	0.000	-0.001	0.000	0.000	-0.001	-0.002
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)*	(0.001)*
Management share	0.000	0.001	0.000	0.001	0.001	0.003
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)**	(0.001)**
Perceived competition	0.010	0.024	0.010	0.024	0.010	0.024
	(0.010)	(0.026	(0.010)	(0.026)	(0.010)	(0.025)
Size					0.057	0.154
					(0.007)**	(0.020)**
Constant	0.270	-0.332	0.298	-0.203	0.030	-1.082
	(0.060)**	(0.145)*	(0.060)**	-0.145	-0.067	(0.182)**
Observations	2076	2076	2074	2074	2074	2074
R-squared	0.44	0.51	0.44	0.51	0.46	0.52

[8] Robust standard errors in parentheses
* significant at 5% level; ** significant at 1% level

Table A8. Chicken or egg: Lagged TFP and change in exports[9]

	Change in exports	Change in exports	Change in exports	Exports, % sales	Change in exports	Exports, % sales
Lagged export status				28.480		26.914
				(1.110)**		(1.260)**
Lagged export , %	-0.204	-0.246	-0.207		-0.224	
	(0.022)**	(0.031)**	(0.022)**		(0.023)**	
One-period lagged TFP1/TFP2	2.783		1.165	2.484	0.014	1.927
	(0.648)**		(0.278)**	(0.381)**	-0.330	(0.396)**
Two-period lagged TFP		3.205				
		(1.049)**				
Age	0.000	0.009	-0.001	-0.041	-0.015	-0.055
	(0.010)	(0.015)	(0.010)	(0.017)*	(0.010)	(0.017)**
Foreign share	0.068	0.047	0.066	0.207	0.055	0.197
	(0.029)*	-0.040	(0.029)*	(0.042)**	-0.029	(0.042)**
State-owned share	-0.004	-0.014	-0.005	0.005	-0.014	-0.009
	(0.014)	(0.023)	(0.014)	(0.020)	(0.014)	(0.020)
Management share	0.002	-0.003	0.001	0.019	0.013	0.034
	(0.017)	(0.023)	(0.017)	(0.024)	(0.017)	(0.023)
Perceived competition	-0.003	0.297	-0.015	-1.573	-0.083	-1.584
	(0.424)	-0.616)	(0.424)	(0.591)**	(0.422)	(0.589)**
Size					1.423	1.698
					(0.259)**	(0.471)**
Constant	-2.108	-2.868	0.676	6.906	-11.988	-1.858
	-2.426	-3.432	-2.363	(3.516)*	(3.198)**	-3.807

[9]Robust standard errors in parentheses
* significant at 5% level; ** significant at 1% level

Table A9. Productivity decomposition (Olley and Pakes, 1996)

Industry	Year	Weighted mean TFP	Non-weighted mean TFP	Reallocation effect
Metals	2000	2.84	2.01	0.86
	2001	2.67	2.09	0.61
	2002	2.58	2.24	0.46
Chemicals	2000	5.82	3.71	2.28
	2001	6.47	3.94	2.62
	2002	5.87	4.11	1.78
Machinery	2000	3.47	2.25	1.31
	2001	3.54	2.50	1.20
	2002	3.87	2.74	1.18
Paper and wood	2000	5.90	4.75	2.44
	2001	5.95	4.53	2.54
	2002	8.52	5.17	3.35
Const. materials	2000	2.43	1.78	0.94
	2001	3.04	1.98	1.19
	2002	3.18	2.25	1.16
Textiles and footwear	2000	5.14	4.27	1.28
	2001	7.59	4.58	3.18
	2002	6.24	4.82	1.48
Total	2000	3.80	2.69	1.38
	2001	4.27	2.90	1.60
	2002	4.50	3.14	1.41

Table A10. ATT estimation with the Kernel Matching method (bootstrapped standard errors)

Productivity index 1

Treated	Controls	ATT	Std. Err.	t-stat
951	1188	0.046	0.028	1.641

Productivity index 2

Treated	Controls	ATT	Std. Err.	t-stat
951	1179	0.138	0.072	1.915

Table A11. ATT estimation, combining propensity score and Mahalanobis method
(bootstrapped standard errors)

Productivity index 1

Treated	Controls	ATT	Std. Err.	z-stat
951	1278	0.009	0.017	0.560

Productivity index 2

Treated	Controls	ATT	Std. Err.	z-stat
951	1278	0.193	0.061	3.17

Table A12. Size and Productivity.

	Change in size, (t-1)-t	Change in TFP, (t-1)-t
Two-period lagged TFP	0.155	
	(0.032)**	
Change in TFP, (t-2)-(t-1)	0.157	
	(0.045)**	
Two-period lagged size		-0.024
		(0.009)**
Change in size, (t-2)-(t-1)		-0.019
		(0.040)
Age	-0.001	0.000
	(0.000)	(0.000)
Foreign share	0.001	-0.001
	(0.001)	(0.001)
State-owned share	0.000	0.000
	(0.001)	(0.001)
Management share	0.002	-0.001
	(0.001)**	(0.001)
Perceived competition	-0.025	-0.001
	(0.016)	(0.015)
Constant	-0.233	0.138
	(0.079)**	-0.103
Observations	947	981
R-squared	0.11	0.05