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Learning-by-exporting versus self-selection: New evidence for 19 sub-Saharan African countries

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highlights

- Novel dataset of manufacturing and services firms from 19 countries in SSA.
- Parameter identification by difference-in-difference regression on matched firms.
- Comparing outlier-robust methods: trimmed OLS, LAD and MM estimators.
- Evidence for learning-by-exporting of manufacturing firms only when using MM.
- No learning-by-exporting effect for services firms.

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abstract

We examine learning-by-exporting effects of manufacturing and services firms in 19 sub-Saharan African countries. Comparing several outlier-robust estimators, our results provide evidence for positive effects in the manufacturing sector when using the MM estimator, but not in the services sector.

1. Introduction

A large number of empirical papers in recent years have used firm- and plant-level data to examine the relation between firms' performance and their export activities. The general conclusion from this literature is that exporters tend to perform better across a number of criteria (Wagner, 2007, 2012a). A smaller number of studies consider data from African countries and confirm the presence of a productivity premium of exporters relative to non-exporters. Sub-Saharan African (SSA) firms, as argued by Van Biesebroeck (2005), may benefit from foreign activities more than firms in other regions, because (i) their production technology is below best practice, providing opportunity to improve through adoption of foreign technology; (ii) their domestic market is small, making foreign sales necessary to exploit scale economies; and (iii) domestic clients postpone or default on payments more often than foreign clients.

Driven by these empirical findings, two alternative but not mutually exclusive explanations have been proposed in the theoretical literature, namely self-selection and learning-by-exporting. Self-selection of the most-productive firms into export activity happens due to additional costs associated with exporting (as in Melitz, 2003). Such costs may include transport, distribution and

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marketing costs, the cost of personnel with skill to manage foreign networks, or production costs from modifying domestic products for foreign consumption. But export activity may also act as a transmission channel of information from abroad, with foreign buyers sharing knowledge of the latest consumer preferences, design specifications and production techniques that might otherwise be unavailable (Blalock and Gertler and 2004, Haidar, 2012).

Our study contributes to this literature by using a novel dataset on a large sample of firms from 19 countries in SSA. While previous studies usually focus on firms in the manufacturing sector, we also consider firms in the services sector. To identify the causal effect between exporting and productivity, we apply propensity score matching of export starters and non-exporters. The use of matching in this context has been pioneered by Wagner (2002) and Girma et al. (2004). As a novelty in this context, we place particular emphasis on the adequate handling of extreme values, since Temouri and Wagner (2013) warn that outliers in firm-level datasets can lead to misleading results.

2. Data

We use data from the Africa Investor Survey (UNIDO, 2012), which was conducted during the year 2010 and covers 19 countries in sub-Saharan Africa, namely Burkina Faso, Burundi, Cameroon, Cape Verde, Ethiopia, Ghana, Kenya, Lesotho, Madagascar, Malawi, Mali, Mozambique, Niger, Nigeria, Rwanda, Senegal, Tanzania, Uganda, and Zambia. The sample was randomly drawn from a survey population of about 60,000 firms after stratifying along the dimensions of country (19 survey countries), size (<50, 50–99, 100+ employees), ownership (domestic or foreign), and sector (ISIC Rev. 3.1, 2-digit).

Out of the 3090 manufacturing firms in the sample, 32% serve foreign markets via exporting, as do 10% of the 2391 services firms. The majority of variables in the dataset cover the last financial year before the data collection took place. In addition, the dataset contains information about the value of sales, the value of exports, and the number of employees for the previous year also. We are thus able to calculate sales per employee as a proxy for productivity for two points in time as well as to identify export starters.

3. Methodology

We combine propensity score matching with difference-in-difference regression similar to Girma et al. (2004). Let ΔY_i denote the growth rate of labour productivity of firm i between the year before the last financial year $t-1$ and the last financial year t. Also let $ExpStart_i \in \{0, 1\}$ be an indicator of whether firm i started to export, i.e. whether it was a non-exporter at time $t-1$ but an exporter at time t. The observed average difference in ΔY_i between export starters and non-exporters is the sum of, first, the average causal effect of starting to export for those firms that do so and, second, the difference between export starters and non-exporters that would also exist if export starters had not started to export.

To estimate the export starter effect without a bias from the self-selection effect, we select a control group of firms out of the pool of all non-exporters by matching on the propensity score, which is the probability P of starting to export conditional on covariates, hence

$$P(ExpStart_i = 1) = F\left(\ln Y_{i,t-1}, \ln Emp_{i,t-1}, Foreign_i, \theta_c, \phi_s\right) \quad (1)$$

where F is the normal cumulative distribution function. The logged productivity of the year before the last financial year, $\ln Y_{i,t-1}$, controls for self-selection into exporting. We also include firms' size in terms of logged employees, $\ln Emp_{i,t-1}$, an indicator of foreign ownership, $Foreign_i$,[2] and sector and country dummies, θ_c and ϕ_s, respectively.[3] The objective is to match export starters to non-exporters with sufficiently close values of the propensity score (Dehejia and Wahba, 2002).

Using only matched observations, we regress productivity growth ΔY_i on the export starter dummy, the level of pre-export productivity $\ln Y_{i,t-1}$, and other pre-export covariates X consisting of ownership, size and size squared, age and age squared, and sector and country dummies:

$$\Delta Y_i = \beta_0 + \beta_1 ExpStart_i + \beta_2 \ln Y_{i,t-1} + \gamma' X + \varepsilon_i. \quad (2)$$

Under the learning-by-exporting hypothesis, export starters are expected to be more productive than non-exporters in year t, given that there is no overall productivity difference in the year $t-1$ by construction. Under the self-selection hypothesis, export starters are not expected to outperform non-exporters, and their only difference is that they realized their opportunity to export.

Wagner (2012b) and Temouri and Wagner (2013) warn against a lack of attention to the presence of extreme observations within the firm-level literature on export premia, as they can have a large influence on the estimated parameters when using the Ordinary Least Squares (OLS) estimator. In response to this shortcoming of OLS, a number of alternative estimators have been developed that are less sensitive to extreme observations. In this letter, we report results from trimmed OLS regression (excluding the first and the last decile of every continuous non-fractional variable), least absolute deviations (LAD) regression, and MM regression.

The MM-estimator is based on the broad class of M-estimators introduced by Huber (1964), which are obtained as the minima of sums of functions of the data. Depending on the type of estimator, the approach involves giving a different contribution of each residual to the objective function, thus allowing outlier observations to have a lower weight in the objective function. The MM-estimator, introduced by Yohai (1987), is an extension of the M-estimator that is more robust to outliers in the explanatory variables. In our analysis, we adopt the implementation method of Verardi and Croux (2009).

4. Results

Results for manufacturing firms are presented in the upper part of Table 1. When using one nearest neighbour matching, the estimated trimmed OLS and LAD coefficients for the export starter dummy are positive but insignificant, indicating the absence of learning-by-exporting (columns 1–2). However, these results might be biased due to bad leverage points or clustered outliers. Indeed, the robust MM-estimator yields a positive and significant learning-by-exporting effect, suggesting a productivity improvement of about 13% (column 3). When relaxing the matching restrictions by considering five nearest neighbours, hence allowing for larger pre-export differences, the learning-by-exporting effect diminishes (columns 4–6). This trend continues when selecting 10 or 15 nearest neighbours (not reported here).

This estimated immediate learning-by-exporting effect of 13% for manufacturing firms is rather low compared to the exporter premium of 40%–50% when running unmatched OLS regressions in productivity levels (Foster-McGregor et al., 2014). We cannot test for additional lagged learning effects for the firms in this dataset, but studies for other countries (including Girma et al., 2004) show

2 A firm is defined as foreign-owned if the share of foreign ownership is 10% or more. In the dataset, information on foreign ownership is only available at time t, which we use as a proxy for time $t-1$.

3 Girma et al. (2004) also include the wage level in time $t-1$, which is not available in our dataset.

Table 1
Dependent variable: Productivity growth (trimmed OLS, LAD, MM; 1 and 5 nearest neighbours).

	(1) 1 NN	(2) 1 NN	(3) 1 NN	(4) 5 NN	(5) 5 NN	(6) 5 NN
	OLS ΔY	LAD ΔY	MM ΔY	OLS ΔY	LAD ΔY	MM ΔY
Manufacturing firms						
ExpStart	0.133	0.114	0.125***	−0.039	−0.015	0.070
	(0.133)	(0.182)	(0.025)	(0.082)	(0.069)	(0.051)
$\ln Y_{t-1}$	−0.086	−0.140	−0.115***	−0.109***	−0.106***	−0.050*
	(0.066)	(0.116)	(0.029)	(0.034)	(0.037)	(0.029)
Constant	−1.052	−0.680	0.199	1.252**	0.661	0.213
	(1.050)	(1.979)	(0.851)	(0.604)	(0.473)	(0.841)
Observations	112	119	119	287	309	309
(pseudo-)R^2	0.399	0.243		0.243	0.094	
Adj. R^2	0.0866			0.126		
Services firms						
ExpStart	0.018	0.009	0.034	0.122	0.072	0.008
	(0.234)	(0.238)	(0.026)	(0.090)	(0.098)	(0.051)
$\ln Y_{t-1}$	−0.381***	−0.207	−0.008	−0.104***	−0.076*	0.002
	(0.139)	(0.142)	(0.016)	(0.033)	(0.041)	(0.013)
Constant	5.177**	1.918	−0.198	2.283***	1.295**	0.106
	(2.064)	(1.979)	(0.447)	(0.529)	(0.636)	(0.387)
Observations	94	95	95	240	256	256
(pseudo-)R^2	0.477	0.159		0.266	0.0711	
Adj. R^2	0.202			0.153		

All regressions include country and sector dummies, a foreign ownership dummy, pre-export size and size squared (number of employees), age and age squared (years). Standard errors in parentheses (heteroscedasticity-robust for OLS and MM, bootstrapped for LAD).
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

that learning effects rather take place immediately. Taken together, these results suggest that export entry significantly increases productivity of firms in the 19 SSA countries, but that self-selection into export markets accounts for most of the productivity differences between exporters and non-exporters. Aside from that, the negative and significant coefficient on the initial level of productivity suggests the presence of productivity convergence among firms as found in Girma et al. (2004). Other covariates are mostly insignificant at conventional levels.

The lower part of Table 1 presents the results for services firms. The export starter coefficient is insignificant for all estimators, in particular for the MM-estimator with 1 nearest neighbour, where the estimate is also much smaller than for manufacturing firms (column 3). Hence, no learning-by-exporting can be observed for services firms, although this conclusion has to be tempered due to the low number of export starters in the service sector in our dataset.

5. Conclusions

Our study adds to the literature by providing limited evidence for the presence of a learning-by-exporting effect for manufacturing firms in 19 SSA countries. This effect is only visible when using the outlier-robust MM estimator. The estimated magnitude of the productivity gain due to export entry is low compared to the productivity differential between exporters and non-exporters reported by other studies, suggesting that this differential is to a large extent still determined by self-selection effects. For firms in the services sector, however, no learning-by-exporting effect can be detected, leaving the observed differences entirely to self-selection effects.

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