ECONOMIC RESEARCH FORUM
منتدى البحوث الاقتصادية

2017

working paper series

FIRM PRODUCTIVITY, TECHNOLOGY AND EXPORT STATUS, WHAT CAN WE LEARN FROM EGYPTIAN INDUSTRIES?

Mohamed Chaffai and Patrick Plane

Working Paper No. 1134

FIRM PRODUCTIVITY, TECHNOLOGY AND EXPORT STATUS, WHAT CAN WE LEARN FROM EGYPTIAN INDUSTRIES?

Mohamed Chaffai and Patrick Plane

Working Paper 1134

September 2017

The authors thank Patricia Augier, Nancy Benjamin, Simone Bertoli, Olivier Cadot, Shanta Devarajan, Jim de Melo, Ishac Diwan, Michael Gasiorek, Mustapha Nabli, for valuable comments on an earlier version of the manuscript. The paper also benefited from the feedback of participants to the 23rd Annual Conference of the Economic Research Forum held in Amman on March 2017.

Send correspondence to:
Mohamed Chaffai
University of SFAX, UREP and ERF
Lep.chafai@fsegs.rnu.tn

First published in 2017 by
The Economic Research Forum (ERF)
21 Al-Sad Al-Aaly Street
Dokki, Giza
Egypt
www.erf.org.eg

Abstract

We explore to what extent the export status and technological choices are related to firm Total Factor Productivity (TFP). Egyptian industrial firms are investigated for the period 2003-2008. The dataset is stratified on five manufacturing industries. Technology being an unobserved phenomenon, a Latent Class Model (LCM) is used to identify its heterogeneity within and across sectors. Translog, Cobb-Douglas, and a mixture of these specifications are used for the estimation of LCMs. Over the five industries, two technology classes prove to be statistically significant. One class provides higher firm productivity levels and is potentially shared by both exporters and non-exporters. Whatever the technology class, except for Food Processing, exporters are found, on average, to have a higher productive performance than non-exporters. Taking into account the potential self-selection effect over the whole sample, Propensity Score Matching (PSM) suggests that the difference is not significant for Food Processing, but varies in the other sectors from 9% in Metal to 32% in Chemistry. When the sample is restricted to labor-intensive technology, which is the largest in terms of number of observations, the premium of export status is about 10%.

JEL Classification: F1

Keywords: Egypt; Manufacturing; Firm Production; Productivity; Technological Choice; Exports

ملخص

نستكشف مدى ارتباط حالة التصدير والخيارات التكنولوجية بإجمالي إنتاجية عوامل الإنتاج وخاصة للشركات الصناعية المصرية للفترة 2003-2008 لمجموعة من البيانات تخص خمس صناعات. ولأن التكنولوجيا ظاهرة غير مرصودة، يتم استخدام نموذج الطبقة الكامنة لتحديد عدم التجانس داخل وعبر القطاعات. ونستخدم وظيفة كوب دوغلاس وخليط من هذه المواصفات لتقدير إجمالي إنتاجية عوامل الإنتاج. وعلى مدى خمس صناعات، أثبتت فئتان من التكنولوجيا أهمية كبيرة إحصائيا. فالفئة الواحدة توفر مستويات إنتاجية أعلى، ويمكن أن يشارك فيها كل من المصدرين وغير المصدرين. ومهما كانت فئة التكنولوجيا، باستثناء تجهيز الأغذية، فإن المصدرين يجدون في المتوسط اداء إنتاجيا أعلى من غير المصدرين. مع الأخذ بعين الاعتبار تأثير الاختيار الذاتي المحتمل على العينة بأكملها، تشير مطابقة نقاط الميل إلى أن الفرق ليس كبيرا بالنسبة لتجهيز الأغذية، ولكنه يختلف في القطاعات الأخرى من 9 في المائة في المعادن إلى 32 في المائة في الكيمياء. عندما تقتصر العينة على التكنولوجيا كثيفة العمالة، وهي أكبر من حيث عدد الملاحظات، والعلاوة على حالة التصدير حوالي 10 في المائة.

1. Introduction

The relationship between exports and productivity has been studied at length since Feder's influential 1983 paper. The conventional wisdom is that firm export status is positively related to technical efficiency or economies of scale, and in a dynamic frame, to technical progress (i.e. the shift of the production frontier over time). From an empirical standpoint, the specific role of the technology, that is the knowledge of techniques, skills, methods and processes that can be embedded in machines operating without detailed knowledge of their workings, has been largely overlooked. Such an approach can be criticized, especially for developing economies where market imperfections lead to heterogeneous production methods. As mentioned by Griliches (1957) and Orea and Kumbhakar (2004), if the econometric specification does not account for technological differences, a potential bias arises about the origins of firm productivity components. This results in a misinterpretation of the driving forces of the productive performance, and wrong prescriptions about the way to reach the best productive state of art (c.f. Sauer and Morrison, 2013). As far as we know, the role of technology has rarely been taken into account on an empirical basis, at least for developing economies. When it has been, sampled firms have generally been broken down into different classes according to *ad hoc* thresholds, generally based on the capital to labor ratio or the firm size.

In the African context dealt with in this paper, Bigsten *et al*. (2001) use a sample of four countries to explore the relationship between firm productivity levels and exports. All firms are placed under a common stochastic production frontier *à la* Battese and Coelli (1995). The impact of production technology being ignored, productivity differences are seen as wholly attributable to the technical efficiency effect. In the same vein, Söderbom and Teal (2003) investigate firms from nine countries and show that firm export status is positively correlated with firm productivity levels. Following the predictions of the Heckscher-Ohlin model, the cost advantage of African countries is seen in labor-intensive technology, which is perceived as the solution to broadening manufacturing activities. Although the role of the technology is assumed, its own contribution is paradoxically not evidenced as a unique production frontier is considered for all sampled firms. Van Biesebroeck (2005) investigates the export/productivity link using a panel of 1,916 firms from nine low-income sub-Saharan countries. In most firms the production technology lags behind international best practices, suggesting that productivity could be improved by adopting foreign technology and know-how. By using Chow-tests for structural breaks, Van Biesebroeck (2005) establishes that exporters use technology with a higher level of equipment per employee, and higher labor skills supported by formal training programs. The hypothesis that the export status is the sole discriminatory criterion across firms implicitly rejects that non-exporters can implement the efficient technology.

The interrelation between firm export status, technology, and TFP performance is what this paper investigates for five Egyptian industries: Garments, Textiles, Food and Processing, Metal Products, and Chemistry. Data from these industries cover the period 2003-2008. The case of Egypt is interesting for several reasons. The country needs to strengthen the productive basis of its manufacturing sector due to the size of the population in urban areas (over 82% of the national population lives in cities of more than 10,000 inhabitants), and due to the growth rate of the labour force (above 1.6% a year). Although trade liberalization has been extended since the 1990s, part of the Egyptian economy still remains highly protected with potential productivity differences between exporters and non-exporters, and varying levels of technological sophistication.

The objectives underlying this paper are twofold. First, for each sector, we test the hypothesis that Egyptian firms use different technologies with potential implications for TFP levels. The technology grouping is based on finite mixture production function models, the so-called Latent Class Model (LCM) (c.f. Greene 2005; Orea and Kumbakhar 2004; Alvarez and Corral, 2010; Sauer and Morrison, 2013). The LCM is estimated by industry, and all firms are allocated across the empirical set of production functions. The main findings can be resumed as follows. Two technology classes proved statistically significant for each of the five sectors. In addition, if export status is not the only determinant of the technological choice, exporters are nevertheless found to be more productive. Secondly, exporters may have specific characteristics which drive the level of productivity in a way that allows a potential self-selection bias. To avoid this bias, the Propensity Score Matching (PSM) method is used. The results are broadly in line with the existence of a positive effect of the export sector, with TFP differences varying from 30% in Chemistry to 10% in Metal Products. When the matching is restricted to the largest technology class, exporting firms remain more efficient, but the magnitude of the gap, which can be interpreted as a technical efficiency effect, is much lower.

The rest of the paper is organized as follows: Section 2 briefly describes the long-run industrial policy in the Egyptian manufacturing sector, and depicts the five specific industries being considered. Section 3 discusses the Latent Class production function Model (LCM), comments on sector-by-sector econometric regressions, and emphasizes the respective role of technology and export status on firm TFP levels. Section 4 focuses on the self-selection bias of the export status using the PSM method. Section 5 sums up the main empirical conclusions.

2. The Egyptian Industrial Sector and the Database

2.1 An overview of the long-run manufacturing policy

From the 1990s onwards, Egypt sent many signals of structural economic and institutional changes which had limited results because reforms have generally been poorly implemented, overly administered, and infrequently monitored (Rodrik, 2008). Loewe (2013) broadly shares this point of view and mentions that for several decades, Egyptian industry has been highly protected in the institutional frame of a large public sector. Authorities slowly moved to a reform process, providing a stronger role for the private sector and export promotion, with mixed results in terms of job creation and diversification. According to Loewe (2013), firm technology uptake has remained low. Despite the government's effort to diversify the economy, exports still remain concentrated on a few industries as in the early 1960s, with low productive performance, including some sectors such as Textiles where the Egyptian comparative advantage lies (Chaffai, Kinda, and Plane, 2012).

The more recent, post Arab Spring literature has emphasized the political cronyism under the Mubarak regime and its implications for the Egyptian manufacturing sector. Diwan et al (2016) suggest that hundreds of politically connected firms in all the sectors of the economy have been responsible for big losses in business opportunities. Not only were these firms protected from import competition by non-tariff barriers, but they also benefitted from energy subsidies and an easy access to financial resources (Diwan *et al,* 2016). These market distortions positively affected private firm profitability, but contributed much less to the social return with a potential productivity bias that is discussed later.

The industrial sector in Egypt generates between 18% and 20% of GDP. The base of the sector is large, but production and even exports still remain concentrated on a limited number of natural resource-based or labor-intensive products. In 2006, Textiles accounted for 31% of the total industrial production, Chemicals 26%, Metal products 16%, and Food and processing 15%. Although their relative importance has varied over time, these four sectors account for approximately 80% of total industrial value added. Oil and gas have traditionally been the driving force of the modern economy, facilitating the development of industries in nitrogenous and phosphate fertilizers as well as petrochemicals and other chemicals. Textiles and Garments are generally considered as high-labor-intensive industries, whose production consists of a wide range of fiber-based products, including raw cotton, yarn, and fabric, as well as ready-made clothes. For these two sectors, Egypt's attractiveness results from logistical advantages, especially the proximity of European markets with the possibility for firms to be quickly reactive to changing fashions and replenishment. The ready-made garment sector produces for both domestic and external markets. Unlike the Textiles sector, which still remains controlled by public enterprises, downstream activities are in private hands. For example, the public sector accounts for 90% of cotton spinning, but only 60% of fabric production and 30% of garment production. With respect to Food and Processing, the ability of the Agriculture sector to provide fruits and vegetables in the European "off-season" combines with the positive effect of its closeness to Europe. Lastly, the Metal sector produces ferroalloys, gold, aluminum, and steel. The steel industry provides a strategic input for other manufacturing production, such as car manufacturers.

2.2 The enterprise surveys and the characteristics of the dataset

The statistical support for the empirical analysis comes from three World Bank *Enterprise Surveys* covering the period 2003-2008. These surveys were conducted face-to-face with the business owners or top managers. The objective of the interviews was to analyze the productive performance at firm level, and to gauge the impact that a broad range of intra-organizational and external factors play on it. Only manufacturing activities are considered in this paper. This restriction is motivated by our objective of investigating the relationship between technological choice and export status in the realization of the productive performance. Not only are services activities very heterogeneous, but most of them are non-tradable goods. The firms are surveyed in a way which represents the national total number of registered private firms employing at least five employees and located in main cities. This sampling rule means that informal businesses are absent. There is no question that this is a limitation for the statistical inference. However, not only is the information about informal businesses poor and subject to big errors in the measurement of inputs and output, but these businesses are rarely exporters, and have little option in the choice of the technology they use. The private sector should be understood in the broad sense - only firms with 100% state ownership are excluded. The sampling methodology is stratified random sampling. Units are grouped within homogeneous categories, and simple random samples are selected within each of them. The stratification is made according to firm size, as measured by three employment levels: small enterprises (from 5 to 19 employees), medium (20 to 99), and large (100 or more). The importance given to each sector reflects its contribution to the manufacturing sector.

Table 1 provides descriptive statistics for the 3,033 observations. The sample across the five sectors includes a total of 1,830 firms. Since the firm identifier varies from one survey to another, the empirical sample is pseudo panel, although some firms may be observed several times. Across the different sections of this paper, the statistical sample marginally fluctuates (no more than 5%) in relation to the available information on firms and the specification of econometric models. The number of observations also differs across the five industrial sectors in accordance with their respective weight in the total industrial population. The largest sector is formed by the combination of Textiles and Garments. Together, they account for nearly 61% of the observations. The working sample has been "cleaned" of outliers by using the regression diagnostic method, which has been preferred to the choice of a trimming percentage.

Table 1 is organized in a way that allows for the comparison of exporting and non-exporting firms. A large set of variables is considered which are in close relation to the technology. Asterisks refer to the statistical significance of the differences between the two sub-groups. For most of the characteristics considered, major differences are shown. Whatever the industry we look at, firms with a presence in external markets are systematically larger, four to five times larger (and even ten times for Garments), than those working exclusively for domestic markets. In addition, the capital to labor ratio proves to be positively and narrowly correlated with export status, although for Garments the difference is only weakly significant. Exporting firms also more frequently have an ISO certification, benefit from foreign licenses, and use a website. As shown by Correa, Fernandes and Uregian (2010), these technical characteristics are potentially linked to the fact that exporting firms are less subject to financial constraints as evidenced by their easier access to an overdraft facility. All these statistical features probably contribute to explaining why exporting firms outperform the labor productivity of organizations that do not export. Except for Garments, the productivity gap is a big one. Productivity of exporting firms is two to three times higher than for non-exporting firms.

3. Impact of Export Status and the Heterogeneity of the Technology

3.1 Unobserved technologies and the Latent Class Model (LCM)

A single production frontier, where firm technology is not observed, may lead to misleading results on the production function parameters, and on firm productivity measures and its components. Kalirajan and Obwana (1994), tackle the issue by estimating a random coefficient model, where each firm is supposed to have its own technology. An alternative option consists of allocating firms to a set of technology classes through a one-step procedure without any *a priori* information to discriminate technology classes. Two recent methods have been used along these lines. The first one is in relation to the threshold regression literature initiated by Hansen (1996, 1999). According to a threshold variable, the estimation allows a sorting of firms into homogenous groups of technologies. This type of model has been revisited by Lai (2012) and Almanidis (2013) for stochastic frontier models. Over a sampled period, firms have the possibility to switch from one technology class to another and the threshold is determined endogenously. The second method, which is more common in the literature and more appropriate for samples with a limited time dimension refers to the latent class model (LCM) proposed by Orea and Kumbhakar (2004) and Greene (2005) for cost and production stochastic frontiers, respectively. A different version of this model, preferred in this paper, was used by Sauer and Morisson (2013) for "average" production functions. In all cases, the likelihood function is represented by a weighted mixture of firm membership probabilities related to the set of technology classes. Probabilities are time invariant, which means that firms cannot switch from one technology to another over the time frame under consideration.

In order to simplify the presentation, the statistical model (see equation 1) is restricted to the particular case of a two-technology-class model with only one functional form. We hypothesize that production functions can be more or less flexible. With the translog form (*TL*), the flexibility is such that there is no restriction on the substitution or complementarity possibilities across inputs, contrasting with the Cobb-Douglas form where substitutions are limited. In the general specification of the model, π is the firm probability to belong to Class 1 and $(1-\pi)$ to Class 2. As mentioned earlier, firms do not switch technologies over time, which means that π is firm specific. The likelihood function to be maximized is as follows:

$$L(y, x, \beta_1, \beta_2, \pi) = \log\left[\pi\, TL(y|x, \beta_1) + (1-\pi)\, TL(y|x, \beta_2)\ \right] \tag{1}$$

where β_1 and β_2 are the vectors of the production function coefficients, *y* is the output as measured by total sales, and *x* the vector of firm inputs (i.e. the number of permanent employees for labor, the book value for capital, and raw material purchases).

With the latent class stochastic "frontier" model (LCSFM), as in Greene (2005) or Orea and Kumbhakar (2004), the frontier incorporates a composed error term broken down into a technical efficiency effect and the usual random noise. Sauer and Morrison's (2013) specification which is adopted here is more attractive for several reasons. Firm TFP levels are derived from the residuals of the "average" production functions. In doing so, not only do we have fewer parameters to estimate, but we avoid the composed error term of the stochastic frontier model. In this case, a subjective choice has to be made with respect to the statistical distribution of the inefficiency component that potentially interacts with the class membership probabilities. As we assume that the functional forms may differ across the different technology classes this specification makes easier the convergence of the LCM likelihood function.

Using Bayes theorem, we estimate the posterior probability technology class membership by:

$$P(i \in Class1) = \frac{\pi \, TL(y, x, \beta_1)}{\pi \, TL(y, x, \beta_1) + (1 - \pi)\, TL(y, x, \beta_2)} \tag{2}$$

The distribution of the probabilities leads to the classification of firms into class 1 if the probability in (2) is greater than or equal to 50% and into class 2 if less than 50%.

Once the model is estimated, TFPs are calculated as weighted measures by using the coefficients of the production functions and the probabilities of class membership:

$$TFP = \left[\frac{Y}{L^{\beta_{1L}} K^{\beta_{1K}} M^{\beta_{1M}}} \right]^{(P(i \in Class1))} \left[\frac{Y}{L^{\beta_{2L}} K^{\beta_{2K}} M^{\beta_{2M}}} \right]^{(1 - P(i \in Class1))} \tag{3}$$

where, β_{1j}, β_{2j} (j =L,K,M) are input elasticities.

3.2 Estimation and comments of the LCMs

Following Orea and Kumbhakar (2004), the inputs of the production functions are divided by their respective geometric means. Applying this procedure, first order term coefficients of the translog functional form are then interpreted as input elasticities evaluated at the means of the data. Different estimations are run to determine the number of production technology classes as well as the appropriate functional form in each class, which can be flexible, non-flexible or a mixture of both. In the absence of any prior theoretical information, the choice of the adequate model is based on the Akaike Information Criterion (AIC). Table 2 presents the estimated production functions with heterogeneous technologies. For the five manufacturing sectors, the common empirical frame that provides the best econometric fit and which is later used for the TFP analysis is made up of two technology classes with a mixture of translog (TL, Class 1) and Cobb-Douglas (CD, Class 2) specifications (see equation 2). The AIC of the other alternative functional forms are given at the bottom of Table 2.

Most of the sampled firms are likely to belong to Class 1 technology with an average class membership probability denoted by π1 that ranges from 81% for Food to 93% for Garments. Input elasticity coefficients differ across classes. The contribution of intermediate consumption to sales is relatively high, revealing quite narrow firm specializations and the use of various forms of external suppliers. Capital intensity as measured by the elasticity of the capital input is higher in Class 2 with a coefficient varying from 0.1 to 0.29 against 0.02 to 0.07 in Class 1[1]. Differences are also observed in the return to scale across sectors and technology classes. Although the tests are not reported here, the hypothesis of constant returns to scale is only met for Chemistry (Class 1) and Garments (Class 2), at the 99% and 95% level of confidence, respectively. This outcome is consistent with the presence of an imperfect competition hypothesis, and the results highlighted by Tybout (2000) in his survey on developing country firms. Therefore, the two technology classes differ whatever the sector we look at, with a significant potential impact on average firm productivity levels. Compared to Class 1, Class 2 TFP kernel distributions (equation 2) are skewed to the right and display a higher productive performance enhanced by the technological gap (Appendix 2).

[1] Later in the text, on the basis of input production function elasticities, Class 2 is referred to as capital intensive technology while Class 1 is defined as labor intensive.

Table 3 sheds light on the factors underlying firm technology class assignment. The probabilities[2] of implementing the more efficient Class 2 technology are correlated with some firm characteristics. The presence of an ISO certification and a foreign license prove significant for three sectors, especially for Garments. The recourse to outsourcing, the promotion of new products, and the use of a website are statistically significant, but only for two sectors. The correlation between class membership probabilities and capital/labor ratio, it is not clear, in line with the controversial arguments mentioned above in the Introduction. This ratio is not significant for Chemistry and Metal, but positive and significant for Food and Processing. The main lesson that we draw from Table 3 is that technological choice is a multidimensional phenomenon that cannot be reasonably restricted to only one variable such as the capital/labor ratio.

In Table 4, the technology classes are analyzed in relation to the productive performance, the export status, and some firm characteristics. Marked differences are evidenced across the two technology classes. Except for Textiles (5.9%), the proportion of exporting firms that are likely to be in this Class ranges from 8.1% (Garments) to 14.8% (Food and Processing) against 4% and 12.5% for non-exporters. Overall, across the five Egyptian manufacturing sectors, unlike what Van Biesebroeck (2005a) finds for sub-Saharan African countries, the most productive technology proves not specific to exporting firms. In their combination of inputs, many Egyptian entrepreneurs have favored the use of abundant and cheap unskilled labor, in accordance with the predictions of the Heckscher-Ohlin model that a country should export goods primarily using abundant factors. For some firms, the choice of input labor mobilization can also be seen as a constraint in an environment where informational issues and market imperfections make access to financial resources unlikely.

With respect to productive performance, both the TFP level and the partial productivity of labor (Y/L)[3] are much higher in Class 2. A potential implication of this result is that some firms using this technology, but working exclusively for domestic Egyptian markets, could probably compete successfully in the global marketplace. This comment has however to be qualified for at least two reasons. First, and this argument more specifically applies to large firms, as mentioned earlier politically connected firms have generally worked for the domestic market in an environment with productivity levels biased by price distortions. Indeed, protection increased the market value of sales while firms also benefited from cheap capital and energy inputs (c.f. Diwan et al, 2016). These advantages have been only partially eroded by some political counterparts such as strong pressure to create jobs, which contributed to lowering the technical efficiency. The second reason concerns small and medium-sized businesses (SMEs). To benefit from the opportunities of external markets, SMEs have to cover fixed and sunk costs. It is worth noting that except for Textiles, non-exporting firms of Class 2 are two to eighteen times smaller than their export counterparts. Accordingly, although some firms have the necessary productive performance to export, a major hindrance can be the cost to access external markets. So far, cooperation between small firms has been limited, and neither the efforts of the State, nor those of the professional organizations, have been able to reduce the costs of informational issues and collective action. In some sectors such as Garments the problem has been met through subcontracting and networking arrangements. Foreign investors have often helped the entry into global value chains by introducing the standards of advanced technologies.

Across the five sectors, exporting firms are the most productive with a larger export premium in Class 2. The largest difference is for Chemistry where the productivity level is more than

[2] This probability is derived from the LCM. It is equal to one minus the probability of belonging to Class 1 from equation (2)

[3] Firm TFP is a weighted measure of those obtained with the two technological classes, while partial labor productivity is an unweighted measure.

twice as high. From Table 4, as mentioned above, firm size matters. In all sectors and technologies, except Textiles (Class 2), exporting firms have the largest permanent labor force, especially in the labor-intensive Class 1. By contrast, there is no obvious conclusion with respect to firm age. On the one hand, young firms are likely to be innovative and reactive to seize the opportunity of new production methods, but on the other hand, old firms have the benefits of more experience, as well as an easier access to external financial resources. The number of firms located in Cairo varies a lot across the five sampled sectors. A majority of those in Garment are established in the capital city, whatever the technology they implement and wherever their markets are. This situation contrasts a lot with the Food and Processing industries for which location in Cairo is marginal, especially for firms which are likely to be in Class 2. Regarding the export intensity, as measured by the percentage of the output traded in external markets, Garments is different from the other sectors, with a very high percentage, more than 76 %. Export intensity is also high in Textiles (52.9%, Class 1) or Food and processing (47.6%, Class 2), but with a substantial difference across technology classes. Last but not least, for the five sectors, the export status goes hand-in-hand with a long experience in external markets that ranges from 9 to 17 years, and suggests that entering external markets efficiently is not easy. The questions of the informational issue and organizational failure that were raised above still remain relevant: what is the best channel for non-exporting firms to gain the critical export knowledge and to what extent can they do it with the capabilities of their own human resources?

4. Comparison of firm TFP levels across Egyptian industries

4.1 Firm TFPs and covariates

Table 5 sheds some light on the factors in relation to firm TFP levels. Estimated coefficients cannot be rigorously interpreted as evidence of causality. The variables of primary interest are the likelihood of implementing the most efficient Class 2 technology, and two variables reflecting the specific potential impact of exports as measured either by a dummy variable or export intensity (i.e. percentage of export sales). The model controls for heterogeneity across sectors as well as the year of implementation of the survey by dummy variables. In the econometric specifications, the baseline regressions (models 1, 2) are augmented with some covariates. From model 4 to 8, as a sensitivity test, we relax the methodological constraints characterizing the LCM. These models provide alternative regressions results when using a Tornqvist non-parametric measure of firm TFP levels where sales are divided by a weighted average of inputs[4]. Wages and intermediate consumptions are respectively considered for their relative contribution to sales, capital input having the complement of unity. On the one hand, non-parametric measures are calculated restrictively under the constant returns to scale hypothesis. On the other hand, they do not need the specification of a functional form, and are not affected by a potential endogeneity bias of inputs that would require the use of Olley and Pakes's (1996) or Levinshon and Petrin's (2003) methods[5].

In the different specifications of Table 5 where firms are combined with dummy variables for sectors and years of surveys, both the technology and the export status are positively and significantly correlated with TFPs, including when the specification is augmented with additional covariates. Under the hypothesis than the causal direction is not problematic an increase of 10% of the probability of belonging to Class 2 would be associated with an average productivity level increase of about 5%. Regarding exporters, on average, their TFP is 10% above non-exporters. Substituting export intensity for the export dummy does not improve the

[4] It goes without saying that a non-parametric measure of TFP is not a better approach. The discussion of the respective merits of the two methods can be found in many textbooks, for example in Coelli et al (1998).

[5] Although these two methods have been extensively used not only can they not be implemented in the framework of the LCM we refer to, but they require a time dimension that we do not have in our empirical context.

quality of the correlations. Therefore, and for two potential reasons, the idea that the impact is conditional upon the intensity of export in firm activity is rejected. First, because it is likely to be volatile, a one-year export to output ratio is not necessarily a structural one; second, the geographical destination also matters. Exporting to developed countries means fierce competition. By contrast, competition is much more limited, and consumers less demanding in terms of quality of goods, when Egyptian firms work for their less-developed close neighbor countries. The geographical distribution of exports then potentially means different pressures on both productivity and quality levels. Unfortunately, the dataset is too poorly documented to test this argument.

4.2 Export status and the Propensity Score Matching (PSM)

TFP levels can be more formally compared by preventing the risk of a selection bias. Exporting firms may have better productive performance due to their initial characteristics which promoted this status. To correct such a potential bias the non-experimental PSM method is used (Rosenbaum and Rubin, 1983). Firms are matched and compared according to common features evidenced in the distribution of probabilities of a logit model (see Appendix 1). The matching procedure is performed only on the sub-sample of exporters and non-exporters that belong to the common support. Several algorithms can be considered, the most common being the non-parametric kernel, the nearest neighbor, and the radius. The non-parametric kernel algorithm compares the TFP levels of exporters to a weighted average of non-exporters. The weighting pattern is determined by the kernel distribution of TFPs and corresponds to firms having close propensity scores. The main limitation of this method is that all firms are included in the matching, although good matches receive a heavier weight than poor ones. With the nearest neighbor method, every exporter is matched with one or *n* non-exporters. The radius algorithm limits match to only the nearest neighbors within the caliper. There is no simple rule of thumb to determine the best algorithm for matching. All of them are asymptotically equivalent, but potentially different, especially for small samples. Therefore, different matching algorithms are implemented here as a robustness check to test the consistency of the findings.

PSM procedures have been used to address the following questions. First, does TFP performance differ between exporting and non-exporting firms which share common characteristics? Second, given the technology, the most natural transmission channel probably being the level of technical efficiency, which would increase due to the stimulation of external competition, do exporters demonstrate higher productive performance? Because the number of observations is large enough for the empirical analysis for Class 1, but not for Class 2, comparisons related to this question are only made for technology Class 1.

Table 6 contains the most important information on exporters and non-exporters, including the TFP premiums and PSM test results. The last column on the right reports the “balancing properties” of the data. Following Sianesi (2004) and Bertoli (2014), we re-estimate the propensity score on the matched sample alone. The difference between the pseudo-R2 on the unmatched and matched sample gives us a measure of the extent to which the estimated propensity score distribution effectively balances the covariates. The balancing properties are satisfied at the 95% level of confidence over the full sample. In a few cases, and only with the nearest neighbor algorithm, it is not significant at 90% for Garments and Textiles when the empirical sample is restricted to the Class 1 technology.

As can be shown from the upper part of Table 6 where the full sample is considered across the two technologies, in twelve out of the fifteen comparisons, exporting firms prove more productive than their counterparts. TFP differences are statistically significant and quite large: more than 30% in Chemistry, about 20% in Garments and Textiles, and 10% in Metal. The matching procedures give consistent results, including for Food and food processing, where the differences are not negligible and not statistically significant, suggesting strong heterogeneity within this sector. In the lower part of Table 6, matching is restricted to firms of Class 1. The number of observations in this class has the valuable advantage of being large enough to allow for comparisons for every manufacturing sector. The application of these tests for Class 2 is problematic due to the limited number of observations, especially for exporting firms. Given the technology, TFP gaps can be interpreted as a technical efficiency effect, although there is room for alternative impacts coming from economies of scale or price differences in relation to non-homogenous products. In this analytical framework, the TFP differences are much less, except for Textiles, Garments, and Chemistry, where the premium of the export status varies from 8.5% to 14.9%. For the two other sectors, the results are inconclusive, no matter which algorithm we consider.

5. Conclusion

Our objective in this paper has been to analyze the role of export status and technologies on firm TFP levels. The formal Egyptian manufacturing sector has been considered over the period (2003-2008). Technology being unobservable, the latent class production function model (LCM) has been used. Firms are statistically allocated to a set of estimated technologies and their productivity level determined through the estimated residuals. Some broad conclusions emerge from the empirical analysis. First, for each of the five sectors, two different technology classes are identified. On the basis of input elasticities of the LCM production functions, each manufacturing sector has a labor-intensive technology class (Class 1), and a capital-intensive one (Class 2). The TFP level of Class 2 proves to be significantly higher. Second, Exporters and non-exporters are in both technology classes. Firm membership of the capital-intensive technology class is correlated with the presence of a wide a range of factors, such as a foreign license, an ISO certification, or the promotion of new products. Accordingly, exporting status does not appear to be a crucial criterion for the choice of the production method. Third, across the two identified technology classes and the five sectors, exporting firms are more productive than their non-exporting counterparts. To control for a potential selection bias in relation to exporting firm characteristics, the PSM method has been used. Over the full sample, with some variations according to the sector, as well as the matching algorithm we use, except for Food, productivity levels are found to be in favor of exporters. The TFP differences vary from 9% (Metal) to 32% (Chemistry). When we restrict the empirical analysis to the large subsample of labor-intensive firms, the TFP differences, which can be interpreted as the technical efficiency effect, are less obvious. The export premium is about 10% for three sectors (Chemistry, Textiles, and Garments).

What kind of practical recommendations do these results lead to? At first glance, some non-exporting firms could be successful in external markets, especially those with Class 2 technology where productivity levels are quite high. However, the Egyptian industrial sector is far from being homogenous, and in a context of imperfect markets firm unit cost has to be analyzed with great care as it matters more than TFP level *per se*. In addition, beyond market imperfections and price distortions, accessing international markets is a challenging issue for SMEs. Except for Textiles, and whatever the technology they use, non-exporting firms are several times smaller than exporting ones, especially those with Class 1 technology. As a result, many SMEs are unlikely to be able to meet the fixed and sunk costs of an export strategy. Beyond the improvement of public governance, promoting exports requires reducing informational costs and coordination failures. Achieving this objective with a "weak State" calls for strengthening the ties within the private sector. If cooperation is unlikely to emerge when firms perceive themselves as competitors in domestic markets, the problem of "collective action" is likely to be smaller if all parties can expect high payoffs from export activities. Trust is therefore crucial to coordinate small firms around an export strategy, together with the use of the optimal technology which is not necessarily a capital-intensive one. This could be achieved, for example, by a financial support of professional bodies that complement the role of the chambers of commerce. Another avenue would be to leverage the role of foreign firms through subcontracting activities. Indeed, repeated contractual arrangements provide opportunities for direct and indirect exports; making the dissemination of efficient technology easier.

References

Almanidis, P. (2013). Accounting for Heterogeneous Technologies in the Banking Industry: A Time-varying Stochastic Frontier Model with Threshold Effects. Journal of Productivity Analysis, 39(2), 191-205.

Alvarez, A., & Corral J. D. (2010). Identifying different technologies using a Latent Class Model/ extensive versus intensive dairy farms. European Review of Agricultural Economics, 37(2), 231-250.

Aw, B. Y., & Hwang, A. R. (1995). Productivity and the Export market: A Firm-Level Analysis. Journal of Development Economics, 47(2), 313-332.

Battese G., Coelli T. (1995). A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Model for Panel Data. Empirical Economics, 20, 325-332.

Beblawi, El. H. (2008). Economic Growth in Egypt: Impediments and Constraints (1974–2004). Commission on Growth and Development. Working Paper No 14. Washington: International Bank for Reconstruction and Development, World Bank.

Bernard, A. B., & Jensen, J. B. (1995). Exporters, Jobs and Wages in US Manufacturing 1976-87. Brookings Papers on Economic Activity Microeconomics, 67-119.

Bernard, A. B., & Jensen, J. B. (1999). Exceptional exporter performance: cause, effect, or both? Journal of International Economics, 47, 1–25.

Bernard, A. B., & Jensen, J. B. (2004). Why Some Firms Export. Review of Economics and Statistics, 86(2), 561–69.

Bertoli, S., & Marchetta, F. (2014). Migration, remittances and poverty in Ecuador. Journal of Development Studies, 50(8), 1067-1089.

Bigsten et al (2001). Are there efficiency gains from exporting in African manufacturing? in Fosu, A., Nsouli, S., and Varoudakis, A., eds, Policies to Foster Manufacturing Competitiveness in Sub-Saharan Africa. Paris: OECD Development Centre.

Bigsten, A., Collier, P., Dercon, S., Fafchamps, M., Gauthier, B., Gunning, J. W., Oduro, A., Oostendorp, R., Pattillo. C., Söderbom. M., Teal, F. & Zeufack, A. (2004). Do African Manufacturing Firms Learn from Exporting? The Journal of Development Studies, 40 (3), 115-141.

Bustos, P. (2011). Trade liberalization, Exports and technology upgrading evidence of the Impact of MECOSUR on Argentinian Firms. American Economic Review, 101, 304-340.

Clerides, S., Lach S., & Tybout J. (1998). Is Learning by exporting important? Micro-Dynamic Evidence from Colombia, Mexico and Morocco. Quarterly Journal of Economics, 113 (3), 903-947.

Chaffai, M., Kinda, T., & Plane, P. (2012). Textile Manufacturing in Eight Developing Countries: Does Business Environment Matter for Firm Technical Efficiency? Journal of Development Studies, 48 (10), 1470-1488.

Coe, D., & Helpman, E. (1995). International R&D spillovers. European Economic Review,39, 859–887.

Coelli, T., Prasada Rao, D., & G. Battese. (1998). An Introduction to Efficiency and Productivity Analysis, Kluwer Academic Publishes, Boston.

Correa, P. G., Fernandes, A. M., & C. J. Uregian (2010) Technology Adoption and the Investment Climate: Firm-Level Evidence for Eastern Europe and Central Asia. The World Bank Economic Review, 10, January 2010.

Diwan. I, Keefer. P. & M. Schiffbauer (2016). Pyramid Capitalism: Cronyism, Regulation, and Firm Productivity in Egypt, Working Papers, 96038, Inter-American Development Bank.

Fafchamps, M., Hamine S. E. (2008). Learning to Export: Evidence from Moroccan Manufacturing, Journal of African Economies, 17(2), 305-355.

Feder, G. (1983). On Exports and Economic Growth. Journal of Development Economics. 12 (1-2), 59-73.

Hansen, B. E. (1996). Inference when a nuisance parameter is not identified under the null hypothesis. Econometrica, 64(2):413–430.

Hansen, B. E. (1999). Threshold effects in non-dynamic panels: estimation, testing, and inference. Journal of Econometrics, 93 (2), 345–368.

Ghoneim, A. (2005). Impact of MFA Removal in Egypt, World Bank MNSED. Mimeo.

Griliches, Z. (1957). Specification bias in estimates of production functions. Journal of Farm Economics, 49, 8-20.

Greene, W. (2005). Reconsidering Heterogeneity in Panel Data Estimator of the Stochastic Frontier Model. Journal of Econometrics, 126, 269-274.

Huang, H. C. (2004). Estimation of technical inefficiencies with heterogeneous technologies. Journal of Productivity Analysis, 21, 277-296.

Kalirajan, K. P. & M. B. Obwana (1994). Frontier Production function: the Stochastic Coefficients Approach. Oxford Bulletin of Economics and Statistics, 56, 87-96.

Kumbhakar, S. C., & Lovell. C. A. (2003). Stochastic Frontier Analysis. Cambridge UK, Boston: Cambridge University Press.

Lai, H. P. (2012). Estimation of the threshold stochastic frontier model in the presence of an endogenous sample split variable. Journal of Productivity Analysis, 40 (2), 227-237.

Levinsohn, J., Petrin A. (2003). Estimating Production Functions Using Inputs to Control for Unobservables. Review of Economic Studies, 70, 317-341.

Loewe, M. (2013). Industrial Policy in Egypt 2004–2011 (Discussion Paper No 114). Bonn: Deutsches Institut für Entwicklungspolitik.

Melitz, M. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. Econometrica,71(6), 1695–1725.

Mobarak, A. (2001, October). The Challenges of Sustainable Industrial Development in Egypt. A Country Paper for the World Summit. United Nations Industrial Development Organization (UNIDO), Cairo.

Olley, S. & Pakes A. (1996), The Dynamics of Productivity in the Telecommunications Equipment Industry. Econometrica, 64(6), 1263-1297.

Orea, L. & Kumbhakar, S. C. (2004). Efficiency measurement using stochastic Frontier latent class model. Empirical Economics, 29, 169-183.

Rodriguez, F. & Rodrik D. (1999). Trade Policy and Economic Growth: A Skeptic's Guide to Cross-National Evidence (NBER Working Paper No 7081). Cambridge, MA: National Bureau of Economic Research.

Rodrik, D. (2008). The Real Exchange Rate and Economic Growth, Brookings Papers on Economic Activity, 39(2), 365-439.

Roberts, M. & Tybout J. (1997). The Decision to Export in Colombia: An Empirical Model of Entry with Sunk Costs. American Economic Review, 87(4), 545-564.

Rosenbaum, P. R., & Rubin, D. B. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. Biometrika, 70 (1), 41–55.

Salsecci, S. et al. (2008). Egypt: growth potential and business opportunities. Turin: Intesa San Paolo.

Sauer, J., Morisson C. J. (2013). The empirical identification of heterogeneous technologies and technical change. Applied Economics, 45, 1461–1479.

Sianesi, B. (2004). An evaluation of the Swedish system of active labor market programs in the 1990s. Review of Economics and Statistics, 86, 133–155.

Söderbom, M. & Teal F. (2003). Are Manufacturing Exports the Key to Economic Success in Africa? Journal of African economies, 12(1),1-29.

Tybout, J. R. (2000). Manufacturing firms in developing countries: how well do they do, and why? Journal of Economic Literature, 28, 11-44.

Tybout, J. R. (2003). Plant- and Firm-Level Evidence on 'New' Trade Theories, in E. Kwan Choi, and James Harriganeds, Handbook of International Trade, 388–415. Malden, MA: Blackwell Publishing.

Van Biesebroeck, J. (2005a). Exporting Raises Productivity in Sub-Saharan African Manufacturing Firms. Journal of International Economics, 67(2), 373–391.

Van Biesebroeck, J. (2005b). Firm Size Matters: Growth and Productivity Growth in African Manufacturing. Economic Development and Cultural Change, 53(3), 545–584.

Table 1: Average Descriptive Statistics: Exporting and Non-Exporting Firms (2003-2008)

Variable \ Sector	Chemistry	Food and Processing	Garments	Metal	Textiles
	563	**446**	**520**	**746**	**758**
Exporters (observations)	**182**	**135**	**124**	**191**	**570**
Permanent employees	387.6***	377.4***	381.2***	319***	411.6***
Skilled workers (% permanent)	5.6***	9.9ns	32.6***	1.8 ns	13.3ns
Labour productivity	60.1***	60.0***	14.1***	51.4***	34.5***
Capital to labour ratio	42***	42.9***	9.0*	30.4**	34.4***
Overdraft facility (% obs)	33.5***	34.8***	26.6***	25.1***	24.5***
Foreign licences (%)	32.4***	19.3***	21.8***	16.8***	19.1***
Quality certificate (ISO) (% obs)	61.5***	68.1***	53.2***	53.4***	60.6***
Use of a website (% obs)	65.9***	55.6***	64.5***	71.2***	66.5***
Experience in exports (years)	13.7	12.4	11.5	11.8	14.9
Exports intensity (% sales)	22.8	32.8	76.9	29.1	51.6
OECD primary destination (% obs)	17.0	23.0	79.0	18.3	67.0
Non-Exporters (observations)	**381**	**311**	**396**	**555**	**188**
Permanent employees	86.5	92.7	31.2	64.3	121.8
Skilled workers (% permanent)	2.7	8.0	20.7	1.1	11.3
Labour productivity	29.9	24.4	11.8	27.9	22.4
Capital-labour ratio	25.1	24.8	7.8	25.1	22.7
Overdraft facility (% obs)	7.1	8.7	3.5	8.3	7.7
Foreign licence (%)	8.1	4.8	2.5	7.0	6.8
Quality certificate (ISO) (% obs)	13.6	12.9	3.0	12.6	10.4
Use of a website (% obs)	22.8	14.8	9.6	23.1	18.6

Note: The t-test, refers to the statistical difference of means between exporting and non-exporting firms. *, 90%; **, 95%; ***, 99%. The sample refers to data over three surveys: 2003-04; 2005-06; and 2007-08; The Table is constructed with observations coming from firms as follows. For Non-Exporters: Chemistry (202), Food and Processing (162), Garments (203), Metal (292), and Textiles (302); For Exporters: Chemistry (96), Food and Processing (74), Garments (64), Metal (98), and Textiles (101). Data are from the World Bank *Enterprise surveys* and cover the period 2003-2008.

Table 2: Estimation of the LCM Across the Five Manufacturing Sectors (2003-2008)

Variable \ Sector	**Chemistry**	**Food and Processing**	**Garments**	**Metal**	**Textiles**
Technology1 (TL)					
Log L	0.17	0.3	0.19	0.08 (4.11)***	0.17
	(8.31)***	(14.90)***	(6.95)***	0.03 (2.35)***	(12.08)***
Log K	0.03	0.02	0.07	0.87	0.05
	(3.04)***	(1.22)***	(4.16)***	(52.35)***	(5.07)***
Log M	0.79	0.71	0.71	0	0.74
	(49.10)***	(47.72)***	(40.82)***	-0.1	(64.18)***
$(\text{Log } L^2)/2$	0.1	0.19	0.16	0.01	-0.02
	(5.22)***	(6.14)***	(2.87)***	(2.26)***	(-2.41)***
$(\text{Log } K^2)/2$	0	0.02	-0.01	0.01	0.01
	(- 0.01)	(2.17)***	(-0.48)	-0.5	-1.57
$(\text{Log } M^2)/2$	0.04	0.09	0.09	-0.03	0.11
	(3.25)***	(7.66)***	(4.05)***	(-2.14)***	(8.25)***
Log L.LogK	0.01	-0.04	0.01	0.01	0.02
	-0.76	(-3.60)***	-0.56	-0.59	(1.75)*
Log L.LogM	-0.06	-0.12	-0.1	0	-0.04
	(- 4.68)***	(-8.65)***	(- 3.80)***	-0.52	(-3.29)***
Log K.LogM	0	0.02	-0.02	-0.22	-0.03
	-0.05	(1.92)**	(-1.02)	(-2.98)***	(-3.91)***
Constant	-0.35	-0.44	-0.45		-0.26
	(-4.53)***	(-6.51)***	(-3.81)***		(-4.50)***
Technology2 (CD)					
Log L	0.2	0.06	0.61	0.61	0.26
	(1.75)*	(1.66)*	(2.71)***	(7.92)***	(2.86)***
Log K	0.19	0.2	0.29	0.1	0.2
	(1.81)*	(3.78)***	-1.54	(2.00)**	(3.12)***
Log M	0.67	0.63	0.43	0.58	0.69
	(8.88)***	(10.60)***	(3.47)***	(12.49)***	(9.77)***
Constant	0.48	1.02	2.47	0.7	1.34
	-0.8	-0.84	-0.8	(1.92)**	(2.75)***
Statistics					
No. observations = 3033	563	446	520	746	758
Log likelihood	-334.24	-199.52	-268.33	-323.45	-330.15
AIC (TL/CD)	714.48	441.03	582.67	692.89	706.31
$\pi 1$	0.84	0.81	0.93	0.83	0.84
Alternative functional forms					
AIC (CD/CD)					
AIC (TL/TL)	741.68	491.83	592.34	695.57	770.51
	894.53	480.68	596.91	698.85	707.33

Source and notes: *World Bank Enterprise Surveys*. L, K, M denote the number of permanent employees, the stock of productive equipment, and the intermediate consumptions, respectively. (TL) and (CD) refer to the translog and the Cobb-Douglas functional forms, respectively. AIC is the Akaike Information Criterion. $\pi 1$ is the average probability for firms to belong to Class 1 technology.

Table 3: Correlations between Class Membership Probabilities (Class 2) and some Characteristics of Technologies

Variable \ Sector	**Chemistry**	**Food and Processing**	**Garments**	**Metal**	**Textiles**
ISO certification	0	0.08	0.12	0.08	0.05
	-0.05	(2.06)**	(3.53)†	(2.82)†	-1.49
New products	0	0.08	0.03	0.06	0.04
	(-0.02)	(2.12)**	-1.13	(1.85)*	-1.44
Upgraded Products	0.01	0	-0.02	0.07	0.02
	-0.37	(-0.05)	(-0.79)	(2.57)†	-0.7
Outsourced products					
	0.05	-0.01	0.13	0.06	0.12
Research and Development department	-0.89	(-0.16)	(2.62)†	-1.29	(2.95)†
Foreign License	0.07	0.01	0.05	0.05	-0.03
	(2.22)**	-0.26	-1.58	-1.58	(-0.98)
Presence of a Website					
	0.06	-0.0 3	0.12	-0.01	0.07
Capital / labor ratio	(1.88)*	(- 0.53)	(3.11)†	(- 0.35)	(1.96)**
Constant	0.06	0.09	0	0	0.01
	(2.17)**	(2.42)**	-0.14	(- 0.03)	-0.38
Survey 2	0	0	0	0	0
	(-2.76)***	(2.22)**	(-0.03)	(-2.69)***	-0.14
Survey 3	0.02	0.08	-0.11	0.07	0.04
	-0.32	(1.99)**	(-1.97)**	(1.63)*	-0.83
No. of Observations	0.04	-0.02	0.01	-0.01	-0.02
	-1.39	(-0.82	-0.3	(-0.31)	(-0.95)
R^2					
	0.07	Omitted	-0.01	0.02	0.03
	(2.11)**		(-0.35)	-0.65	-1.17
	553	447	520	746	758
	0.046	0.047	0.06	0.047	0.042

Notes: Class 2 is the more productive technology class. **Source:** Data are from the World Bank *Enterprise surveys* and cover the period 2003-2008. Student t-tests are in parentheses with the following level of confidence: * (90%); ** (95%); † (99%). Except for capital labor ratio, which is a continuous variable, all the other covariates are expressed under the form of binary variables. Surveys 2 and 3 are dummies; the reference is the first survey in 2003-2004.

Table 4: Firm Characteristics, Export Status and Productivity Across Technology Classes

Sector	Class 1 *Labour intensive* Export	Non-Export	t-test	Class 2 *Capital intensive* Export	Non-Export	t-test
Chemistry (563)	**(163)**	**(347)**		**(19)**	**(34)**	
TFP	4.3	3.8	***	15.3	6.0	***
Y/L	81.7	32.4	***	213.2	128.4	Ns
L	478.5	81.8	***	563.9	222.1	***
Age	25.5	24.9	Ns	26.3	18.5	**
Cairo	22.7%	17.6%	Ns	15.8%	29.4%	Ns
Export intensity	22.2%			28.1%		
Export experience	13.6			14.8		
Food (446)	**(115)**	**(272)**		**(20)**	**(39)**	
TFP	4.7	4.3	*	13.7	9.6	***
Y/L	67.4	18.9	***	125.6	85.7	**
L	325.7	89.4	***	174.8	67.9	***
Age	29	24.5	Ns	21.1	24	Ns
Cairo	7.8%	7%	Ns	0.5%	0.5%	Ns
Export intensity	30.2%			47.6%		
Export experience	11.3			17.8		
Garments (520)	**(114)**	**(380)**		**(10)**	**(16)**	
TFP	4.7	4.1	***	7.0	5.5	Ns
Y/L	24.4	10.8	***	216.4	35.2	**
L	230.8	31.6	***	380	21.3	***
Age	14.5	21.2	***	8.8	22.3	**
Cairo	32.4%	53.4%	***	60%	50%	Ns
Export intensity	76.2%			85%		
Export experience	11.6			9.3		
Metal (746)	**(170)**	**(497)**		**(21)**	**(58)**	
TFP	2.93	2.91	Ns	4.94	3.91	***
Y/L	47.1	29.6	**	119.2	62.27	Ns
L	440	65.3	***	264.7	87.7	***
Age	23.8	21.8	Ns	27.7	26.4	Ns
Cairo	26.5%	32.2%	Ns	52.4%	31%	*
Export intensity	29.2%			28.5%		
Export experience	11.9			11.2		
Textiles (758)	**(177)**	**(505)**		**(11)**	**(65)**	
TFP	4.7	4.1	***	6.0	4.2	***
Y/L	39.7	18.1	***	137.8	67.1	**
L	878.7	166.8	***	245	433	Ns
Age	26.9	25	Ns	15.3	29.3	**
Cairo	8.5%	12.9%	*	18.2%	26.2%	Ns
Export intensity	52.9%			30.9%		
Export experience	15.3			9.5		

Note: TFP: Total Factor Productivity; Y/L: per employee value added; L: Number of permanent employees. Percentage of firms located in Cairo. The export experience refers to the number of years with the exporting status while export intensity is the percentage of sales that are exported. Level of confidence: * (90%) ** (95%) *** (99%).

Table 5: Log Firm TFP Measures and Some Correlates Across the Five Sectors: Egypt (2003-2008)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
		Parametric TFP measures				*Non-parametric TFP measures*		
Export	0.115		0.105		0.172		0.153	
dummy	(8.35) †		(6.01)†		(7.31) †		(5.12) †	
Export intensity		0.002		0.001		0.018		0.001
		(6.61) †		(4.11)†		(4.24) †		(1.96)**
Probability								
Class 2	0.515 (21.9) †	0.511	0.52	0.517	1.242	1.235	1.25	1.24
		(21.5) †	(22.0) †	(21.9) †	(30.7) †	(30.3) †	(30.6) †	(30.3)†
Size								
			-0.08	0				
			(-1.46)	(-0.08)				
Website								
			0.011	0.018			0.029	0.047
			-0.72	-1.12			-1.06	(1.71)*
Industrial zone								
			0.067	0.07			0.0476	0.039
Skilled workers			(4.82) †	(5.03)†			(1.98)**	-1.61
Overdraft facility			0	0			0	0
			-0.6	-0.06			-0.72	-0.59
Foreign licence								
			0.012	0.018			0.028	0.017
Managerial experience			-0.59	-0.93			-0.81	-0.5
Constant			0.039	0.047			0.066	0.081
			(1.82)*	(2.20)**			(1.79)*	(2.20)**
Observations			-0.002	-0.002			0.038	0.001
			(-3.62)†	(-3.44)†			(1.68)*	-1.51
R^2	1. 271							
	(72.9) †	1. 2687	1.45	1.45	1.228	1.232	1.255	1.27
		(71.6)†	(34.1)†	(33.7)†	(41.0)†	(40.5)†	(17.1)†	(17.2)†
	3033							
		3032	2988	2987	3033	3032	2988	2987
	0.3							
		0.3	0.32	0.32	0.26	0.25	0.27	0.26

Notes: *Export*, dummy variable taking the value "1" if the firm directly exports and "0" otherwise. *Export intensity*, ratio of direct exports to current sales. Dummy variables: "1" if the firm is in an industrial zone, has a website, an overdraft facility, a foreign license; Managerial experience: number of years of the top manager; Size: number of permanent employees. Student t-test: † (99%), ** (95%) * (90%). Regressions incorporate dummies for sectors and years of surveys.

Table 6: Firm TFP Levels and the Export Premium: the PSM Method

	Mean Obs	TFP exporters	Mean TFP non-exporters	Statistical difference	Balancing test (p-value)
		Exporters versus non-exporters (full sample, Class1 and Class 2 technologies)			
Chemistry					
- Nearest Neighbor	181/373	5.44	4.11	32.40%	2.74*** 0.48
- Radius	181/373	5.44	4.16	30.80%	2.87*** 0.91
- Kernel	181/373	5.44	4.16	30.80%	2.85*** 0.85
Food & processing					
- Nearest Neighbor	131/302	6.08	5.1	19.20%	1.47 0.41
- Radius	131/302	6.08	5.42	12.20%	1.05 0.48
- Kernel	131/302	6.08	5.47	11.20%	0.97 0.55
Garments					
-Nearest Neighbor	120/394	4.94	4.08	21.10%	2.28** 0.87
- Radius	120/394	5.09	4.18	21.80%	2.64** 0.80
- Kernel	120/394	5.04	4.16	21.20%	2.52** 0.64
Metal					
-Nearest Neighbor	191/548	3.16	2.85	10.90%	2.34** 0.24
- Radius	191/548	3.16	2.89	9.30%	2.28** 0.85
-Kernel	191/548	3.16	2.9	9.00%	2.21** 0.83
Textiles					
-Nearest Neighbor	186/562	4.74	3.92	20.90%	3.96*** 0.08
- Radius	186/562	4.74	3.97	19.40%	4.13*** 0.11
- Kernel	186/562	4.74	3.97	19.40%	4.14*** 0.16
			Exporters versus non-exporters (Class 1 technology)		
Chemistry					
- Nearest Neighbor	162/342	4.15	3.62	14.60%	2.25** 0.27
- Radius	162/342	4.15	3.8	8.90%	1.63 0.73
- Kernel	162/342	4.15	3.79	9.50%	1.78* 0.58
Food and processing					
-Nearest Neighbor	111/264	4.64	5.24	-11.50%	-1.46 0.35
- Radius	111/264	4.64	4.83	-3.90%	-0.63 0.53
- Kernel	111/264	4.64	4.87	-4.70%	-0.75 0.46
Garments					
-Nearest Neighbor	111/378	4.68	4.31	8.60%	0.98 0.05
- Radius	111/380	4.68	4.18	12.90%	1.90* 0.71
- Kernel	112/380	4.68	4.2	6.40%	1.70* 0.58
Metal					
-Nearest Neighbor	170/490	2.94	2.85	3.20%	0.76 0.10
- Radius	170/490	2.94	2.81	4.60%	1.29 0.53
- Kernel	179/490	2.94	2.81	4.60%	1.28 0.42

Table 6: Continued

	Mean Obs	TFP exporters	Mean TFP non-exporters	Statistical difference	Balancing test (p-value)
Textiles					
-Nearest Neighbor	175/498	4.62	4.26	8.50%	1.68* 0.02
-Radius	175/498	4.62	4.02	14.90%	3.87*** 0.78
-Kernel	175/498	4.62	4.06	13.80%	3.40*** 0.60

Note: The t-test provides information about statistical differences among groups of firms. In the last column, by the balancing test, we test whether covariates still discriminate firms after the matching procedure has been done.

Appendix 1

Logit regressions underlying the analysis of exporter and non-exporters according to the Propensity Score Matching (PSM) method

	Chemistry	**Food**	**Garments**	**Metal**	**Textiles**
Log Labor	0.46	0.29	0.61	0.43	0.34
	(7.99) †	(4.33) †	(5.00) †	(8.46) †	(7.74) †
Industrial zone	0.57	0.55	0.61	0.25	0.32
	(4.07) †	(3.53) †	(2.78) †	(1.97) **	(2.60) †
Growth expectation					
	0.53	0.42	0.56	0.51	0.37
Website	(3.63) †	(2.52)**	(2.90) †	(3.82) †	(2.97) †
	0.26	0.72	0.55	0.39	0.82
	(1.71) *	(4.10) †	(2.54) **	(2.68) †	(6.33) †
Skilled Workers					
	0.04	0	0	0	0
Overdraft facility	-1.07	-1.17	-1.2	-0.58	-0.26
	0.43				
Foreign Licence	(2.40)**	0.23	0.11	0.03	0.1
		-1.09	-0.36	-0.16	-0.6
Managerial experience	0.33				
	(1.87)*	0.08	1.11	0	0.48
Constant		-0.28	(3.35) †	(-0.01)	(2.65) †
	0				
	(- 0.61)	0	-0.01	0.02	0.01
No. Observ		-0.21	(- 0.85)	(3.92) †	-1.35
	-1.55				
Pseudo R^2	(-4.01)	-0.91	-1.58	-2.6	-1.31
		(-1.78)*	(- 2.25)**	(-7.20) †	(-3.78)†
	554				
		433	514	739	748
	0.37				
		0.3	0.59	0.36	0.34

Appendix 2

Kernel TFP distributions according to the Latent Class Model (by technology class distributions)