Firm productivity and export status in the Egyptian environment

Mohamed Chaffai
University of SFAX, UREP
Lep.chafai@fsegs.rnu.tn, mechaffai@gmail.com

Patrick Plane
Clermont University of Auvergne CERDI
65 Boulevard François Mitterrand 63000Clermont Ferrand, France
patrick.plane@udamail.fr

December 12, 2016

Abstract

The main objective of this paper is to explore to what extent the export status is related to the technological choice and firm TFP gaps with non-exporters. A sample of 1,830 observations of Egyptian firms is considered over 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 hypothesized for the estimation of LCMs. Over the five industries, two technology classes prove empirically relevant. One provides higher firm productivity levels and is potentially shared by both exporters and non-exporters. Whatever the technology class, except for Food, exporters are found, on average, to have a higher productive performance. Taking into account the potential self-selection effect over the full sample, Propensity Score Matching (PSM) suggests that the gap is not significant for Food and varies in the other sectors from 9% in Metal to 32% in Chemistry. When the sample is restricted to the labor-intensive technology, which is the largest in terms of observations, the premium of the export status is about 10%.

1. Introduction

The relationship between exports and productivity has been studied at length since the influential paper by Feder (1983). The conventional wisdom is that the firm export status is positively related to technical efficiency or scale economies, and in a dynamic frame, to the technical progress (i.e., the shift of the production frontier over time). From an empirical standpoint, the specific role of technology differences across firms has been largely overlooked, which may be restrictive, especially for developing economies where market imperfections mean heterogeneous production methods. As mentioned by Griliches (1957) as well as 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 result in a misinterpretation of the driving force of the productive performance and wrong prescriptions on the way for firms to reach the best productive state of art (see. Sauer and Morrison, 2013). As far as we know, this technological issue has rarely been taken into account on an empirical basis, and when it was, sampled firms have generally been broken down into different classes according to ad hoc thresholds based on the capital labour ratio criterion.

In the African context this paper deals with, Bigsten et al. (2001) refer to 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, Söderbomand Teal (2003) investigate firms from nine countries and show that the 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 viewed in a labor-intensive technology which is perceived as the solution to broaden manufacturing activities. Although the role of the technology is presumed, its own contribution is paradoxically not evidenced as a unique production frontier is assumed 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 is lagging behind international best practices suggesting that productivity could be improved by adopting foreign knowledge and technological know-how. By using Chow-tests for structural breaks, Van Biesebroeck (2005) establishes that exporters actually use a technology with a higher level of equipment per employee, more labor skills supported by formal training programs. This statistical analysis relies on the hypothesis that the export status is the sole discriminate criterion across firms denying the possibility for some non-exporters to 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 to the growth rate of the labor 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 research question underlying this paper is 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) (see. Greene 2005, Orea and Kumbakhar 2004; Alvarez and

Corral, 2010, Sauer and Morison 2012). By industry, the LCM is estimated 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 relevant for each of the five sectors. In addition, if the 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 driving the level of productivity in a way giving room to a potential self-selection bias. To explore this bias, the Propensity Score Matching (PSM) method is used. Results are broadly in line with the existence of a positive effect of the export sector with TFP gaps 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 organised as follows. Section 2 briefly describes the long-run industrial policy in the Egyptian manufacturing sector and depicts the five specific industries. Section 3 discusses the Latent Class production function Model (LCM), comments on sector-by-sector econometric regressions, and emphasises the respective role of the 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 with mixed results as reforms have generally been poorly implemented, overly administered, and infrequently monitored (Rodrik, 2008). According to Lowe (2013), post-2004 industrial policies have promoted investments and exports, but achieved a limited outcome. Firm technology absorption has remained low, complicating the rise of firm productivity and the industrial competitiveness. 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 labour-intensive products.

In 2006, textiles accounted for 31% of the total industrial production versus 26% for chemicals, 16% for metal products, and 15% for food processing. Although their relative importance has varied over time, together, these four sectors account for approximately 80% of the 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 fertilisers as well as petrochemicals and other chemicals. Textiles and Garments are generally considered as high-labor-intensive industries. Production consists of a wide range of fiber-based products, including raw cotton, yarn, fabric, and ready-made garments. With regard to these latter products, Egypt's attractiveness results from some logistical advantages, especially the proximity of European markets and the possibility for firms to be quickly reactive to changing fashions and replenishment. The ready-made garments sector produces for domestic and external markets as well. Unlike the Textile 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 apparel production. With respect to Food Processing, exotic fruits and a wide variety of vegetables shape the production of this sector. Thanks to good climatic conditions, the ability of the Agriculture sector to provide fruits and vegetables in the "off-season" combines its positive effect with the closeness of Europe. With respect to the Metal sector, Egypt is a producer of ferroalloys, gold, aluminium, and steel, the latter relying heavily on rebar demand. The steel industry is a strategic input for other manufacturing products, such as large users like car manufacturers.

For several decades, Egyptian industry remained highly protected in the institutional frame of a large public sector. Authorities slowly moved to a reform process, providing a stronger role to the private sector and export promotion, with mixed results in terms of job creation and diversification. According to Loewe (2013), despite the government's decade-long effort to diversify the economy, in 2004, exports were still as concentrated as in the early 1960s and productive performance remained low, including in sectors where Egyptian comparative advantage stands, such as Textiles (see Chaffai, Kinda, and Plane, 2012).

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 have been conducted face-to-face with the business owners or top managers. The objective of 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 to investigate the relationship between the technological choice and the export status in the realization of the productive performance. Not only are services very heterogeneous but, in addition, most of them are non-tradable goods. Surveyed firms are retained in a way complying with the representativeness of the national number of registered private enterprises employing at least five employees and located in main cities. The private sector must be understood in the broad sense—only firms with 100% state ownership are excluded. The sampling methodology is the 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 (20-99), and large firms (100 or more). Moreover, the importance given to each sector reflects its contribution to the manufacturing sector.

Table 2 provides descriptive statistics about the 3,033 observations. The sample across the five sectors includes a total of 1,830 firms. Since the firm identifier varied from one survey to another, the empirical sample is not a standard panel but a cross-section (pseudo panel), although some firms are observed several times. Across the different sections of the 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 population of industries. The largest sector is formed by the combination of Textiles and Garments. Together, they account for nearly 61% of the total observations. A careful examination of data showed that some observations had highly implausible values affecting statistical results. Accordingly, the working sample has been "cleaned" of outliers by using the regression diagnostic method, which was preferred to the trimming of a certain percentage reflecting the top and the bottom of the production function variables.

Table 2 is organised in a way that allows for the comparison of exporting and non-exporting firms. A large set of variables is considered that may influence the technological choice. Asterisks refer to the statistical significance differences between the two sub-groups. For most of the considered features, major differences are displayed between exporting and non-exporting firms. 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, except for the Garment sector where all firms are associated with a labor-intensive technology, the capital-labor ratio proves positively and narrowly correlated with the export status. Exporting firms also more frequently have an ISO certification, in order to benefit from foreign licences or to use a website. Last but not least, financial constraints do not apply the same way to all enterprises. Access to an overdraft facility more generally reflects the ability of producers to raise money from their external environment. All these statistical features probably contribute to explain why exporting firms seem to outperform the labor productivity of their non-exporting counterparts. Except for Garments, the gap is a strong one, two to three times higher in accordance with higher capital-labor ratios. Therefore, one may hypothesise that productive technologies is heterogeneous across firms and can be a potential source of explanation of their performance. Beyond commenting on the descriptive statistics, the next sections explore in more detail the empirical linkages between variables.

Table 2. Average descriptive statistics: exporting and non-exporting firms (2003-2008)

Variables\Sectors	Chemistry 563	Food 446	Garments 520	Metal 746	Textiles 758
X- 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
Labor productivity	60.1***	60.0***	14.1***	51.4***	34.5***
Capital-labor ratio	42***	42.9***	9.0*	30.4**	34.4***
Overdraft facility (% observations)	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 (%)	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/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
NX-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
Labor productivity	29.9	24.4	11.8	27.9	22.4
Capital-labor ratio	25.1	24.8	7.8	25.1	22.7
Overdraft facility (% observations)	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) (% of obs)	13.6	12.9	3.0	12.6	10.4
Use of a website (% of observations)	22.8	14.8	9.6	23.1	18.6

Note. The t-test, last column on the right, 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 over the sample and come from firms as follows: Chemistry (202), Food (162), Garments (203), Metal (292), and Textiles (302) for non-exporters; Chemistry (96), Food (74), Garments (64), Metal (98), and Textiles (101)for exporting firms. Data are from the World Bank Enterprise surveys and cover the period 2003-2008.

3. Impact of the export status and the heterogeneity of the technology

3.1.Unobserved technologies and the Latent Class Model (LCM)

A single production frontier when firm technology is not observed may lead to misleading results on the production function parameters, and then on firm productivity measures and its components. In some empirical models, as in Kalirajan and Obwana (1994),the solution to this problem is found in the estimation of a random coefficient model, where each firm is supposed to have its own technology. An alternative methodological option consists in 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 in this respect. The first one is in relation with the threshold stochastic frontier models. Over a sampled period, firms have the possibility to switch from one class technology to another. The threshold is not predetermined but derived from the econometric estimation (Lai, 2012; Almanidis, 2013). The second method, which is more current in the literature and more appropriate for samples with a limited time dimension, restricts the technology not to switch over time. The model has been initially proposed by Orea and Kumbhakar (2004) and Greene (2005) in the frame of stochastic production functions. A different version of this model, that will be preferred in this paper, has been proposed by Sauer and Morisson (2013) for "average" production functions. In all cases, the latent class modeling approach is based on finite mixture models where the unobserved technology heterogeneity is represented by a mixture of several distributions weighted by mixing fractions.

For the sake of convenience for the methodological presentation, the statistical model represented in equation (1) is restricted to the particular case of a two-technology-class model. We hypothesize that production functions can be more or less flexible. With the translog form to which equation (1) refers, flexibility is such that there is no restriction at all on the substitution or the complementarities possibilities across inputs. In contrast to the Cobb-Douglas form, substitution possibilities are limited. As technologies are unobservable, the latent class probabilistic model affects each firm to the most likely technology, given the level of its respective inputs and output. In the most general specification form of the model, π is a probability for a firm to belong to the class 1 technology and (1-π) to the class 2. As mentioned earlier, each firm does not switch across technologies over time, which means that π is constant. By referring to the translog technology (TL), the likelihood function to be maximised is as follows:

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

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., number of permanent employees for labor, the book value for capital, and raw material purchases).

With the latent class stochastic "frontier" specifications (LCSFM), as in Greene (2005) or Orea and Kumbhakar (2004), the production frontier concept incorporates a composed error term disentangled into a technical efficiency effect and the usual random noise. The model we use is more parsimonious with respect to the estimated parameters. Firm TFP levels are derived from "average" production functions, and error terms capture the standard random disturbances. Let us mention that even if this specification provide less information than the LCSFM, the derived results are less sensitive to the subjective choice of a particular statistical distribution for the inefficiency component (i.e., half normal, exponential, truncated normal…) which may also interact with the class membership probability. In addition, our specification relies on the estimation of fewer parameters and makes it easier the convergence of the model likelihood function. This advantage is not negligible in an empirical context where the functional form of the production function is not necessarily the same across the different technology classes, an additional source of the unobserved technology heterogeneity across firms.

According to the LCM, each sampled firm is probabilistically assigned to the set of technologies. Using Bayes theorem, we estimate the posterior probability technology class by:

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

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, firm TFP levels are calculated using the coefficients of the production functions and the probability class membership as below:

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

where, β_{1j}, β_{2j} (j =L,K,M) are input elasticities. (the log TFP is a weighted average of each firm's TFP class)

3.2. Estimation and comments of the LCMs

Following Orea and Kumbhakar (2004), inputs are divided by their respective geometric mean. Applying this procedure, first order term coefficients of the translog functional form are then interpreted input elasticities, as it is the case for the Cobb-Douglas form. Different estimations have been run to determine the number of production technology classes as well as the appropriate functional forms. For instance, several specifications of the technology have been considered, flexible or non-flexible forms as well as a mixture of both. The flexible translog form allows the investigation of the technology by testing the significance of coefficients of the second order and the cross product of inputs, while the non-flexible Cobb-Douglas form restricts the elasticity of substitution between inputs to unity. In the absence of any prior theoretical information, the choice of the adequate model has been made on an empirical basis according to the Akaike Information Criterion (AIC). For the five manufacturing sectors, a common empirical frame of reference emerges, made of two empirical production technologies with a mixture of translog (TL, Class 1) and Cobb-Douglas (CD, Class 2) specifications (see equation 2). The AIC relative to the different econometric specifications is provided at the bottom of Table 3. For each manufacturing sector, Table 3 displays the estimated production functions with heterogeneous technologies.

Table 3. Estimation of the LCM across the five manufacturing sectors (2003-2008)

Variables\Sectors	Chemistry	Food	Garments	Metal	Textiles
Technology1 (TL)					
Log L	0.17	0.30	0.19	0.08	0.17
	(8.31)***	(14.90)***	(6.95)***	(4.11)***	(12.08)***
Log K	0.03	0.02	0.07	0.03	0.05
	(3.04)***	(1.22)***	(4.16)***	(2.35)***	(5.07)***
Log M	0.79	0.71	0.71	0.87	0.74
	(49.10)***	(47.72)***	(40.82)***	(52.35)***	(64.18)***
$(\text{Log } L^2)/2$	0.10	0.19	0.16	0.00	-0.02
	(5.22)***	(6.14)***	(2.87)***	(0.10)	(-2.41)***
$(\text{Log } K^2)/2$	- 0.00	0.02	-0.01	0.01	0.01
	(- 0.01)	(2.17)***	(-0.48)	(2.26)***	(1.57)
$(\text{Log } M^2)/2$	0.04	0.09	0.09	0.01	0.11
	(3.25)***	(7.66)***	(4.05)***	(0.50)	(8.25)***
Log L.LogK	0.01	-0.04	0.01	-0.03	0.02
	(0.76)	(-3.60)***	(0.56)	(-2.14)***	(1.75)*
Log L.LogM	- 0.06	-0.12	-0.10	0.01	-0.04
	(- 4.68)***	(-8.65)***	(- 3.80)***	(0.59)	(-3.29)***
Log K.LogM	0.00	0.02	-0.02	0.00	-0.03
	(0.05)	(1.92)**	(-1.02)	(0.52)	(-3.91)***
Constant	-0.35	-0.44	-0.45	-0.22	-0.26
	(-4.53)***	(-6.51)***	(-3.81)***	(-2.98)***	(-4.50)***
Technology2 (CD)					
Log L	0.20	0.06	0.61	0.61	0.26
	(1.75)*	(1.66)*	(2.71)***	(7.92)***	(2.86)***
Log K	0.19	0.20	0.29	0.10	0.20
	(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	0.70	1.34
	(0.80)	(0.84)	(0.80)	(1.92)**	(2.75)***
Statistics					
Nbobs = 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)	741.68	491.83	592.34	695.57	770.51
AIC (TL/TL)	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.

Due to the normalization procedure we made, the estimated input elasticities are positive, but different across classes. Compared to Class1, the high level of the capital elasticity in the Class

2 technology suggests capital-intensive production functions versus labor intensive in the other class. The contribution of the intermediate consumption is however relatively high, revealing narrow specializations with limited backward or forward integration within firms. The average probability for firms to belong to the first translog technology is given by $\pi 1$ and ranges between 81% and 84%, except for Garments where the concentration proves higher (93%). Differences in return to scale across sectors and technology classes are found. The tests are not reported here to save space, but 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 imperfect competition hypothesis and Tybout (2000)'s survey on developing country firms.

As shown in Appendix 2, 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. Probabilities to implement the most efficient Class 2 technology[1] can be correlated with some current firm characteristics reflecting this technology. Table 4 shows that the presence of an ISO certification as well as a foreign license is significant for three sectors, especially for Garments where these variables are statistically significant at the 99% confidence level. The recourse to outsourcing, the promotion of new products, and the use of a website prove significant in two of the sectors studied. For all of the aforementioned variables, regression results are in accordance with our intuition, at least with respect to the sign of the coefficients. The correlation between probabilities and the capital intensity is quite uncertain, in line with some controversial arguments recalled in the introduction of the paper about the complexity of the technology of the firms. Indeed, the capital-labor ratio is non-significant for two sectors, displaying a negative correlation for Chemistry and Metal, and a positive one for only Food and

[1] This probability is equal to one minus the probability to belong to Class 1 from equation (2)

Processing. From the information of this table, we conclude that technology is a multidimensional phenomenon. Accordingly, a high level of equipment per employee remain an ambiguous criterion for separating firms according to the technology they use.

Table 4. Correlations between Class membership probabilities (Class 2) and some characteristics of technologies

Variables\Sectors	Chemistry	Food	Garments	Metal	Textiles
ISOcertification	0.00 (0.05)	0.08 (2.06)**	0.12 (3.53)†	0.08 (2.82)†	0.05 (1.49)
New products	- 0.00 (-0.02)	0.08 (2.12)**	0.03 (1.13)	0.06 (1.85)*	0.04 (1.44)
Upgrade Products	0.01 (0.37)	- 0.00 (-0.05)	-0.02 (-0.79)	0.07 (2.57)†	0.02 (0.70)
Outsourced products	0.05 (0.89)	-0.01 (-0.16)	0.13 (2.62)†	0.06 (1.29)	0.12 (2.95)†
Research and Development department	0.07 (2.22)**	0.01 (0.26)	0.05 (1.58)	0.05 (1.58)	-0.03 (-0.98)
Foreign License	0.06 (1.88)*	-0.0 3 (- 0.53)	0.12 (3.11)†	-0.01 (- 0.35)	0.07 (1.96)**
Presence of a Website	0.06 (2.17)**	0.09 (2.42)**	0.00 (0.14)	-0.00 (- 0.03)	0.01 (0.38)
Capital intensity (K/L)	-0.00 (-2.76)***	0.00 (2.22)**	-0.00 (-0.03)	0.00 (-2.69)***	0.00 (0.14)
Constant	0.02 (0.32)	0.08 (1.99)**	-0.11 (-1.97)**	0.07 (1.63)*	0.04 (0.83)
Surveyed 2	0.04 (1.39)	-0.02 (-0.82	0.01 (0.30)	-0.01 (-0.31)	-0.02 (-0.95)
Surveyed 3	0.07 (2.11)**	Omitted	-0.01 (-0.35)	0.02 (0.65)	0.03 (1.17)
Number of Observations	553	447	520	746	758
R^2	0.046	0.047	0.060	0.047	0.042

Source and notes: Data are from the World Bank *Enterprise surveys* and cover the period 2003-2008. Student t-test, level of confidence: * (90%); ** (95%); † (99%). Except for capital intensity, 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.

In Table 5, by-sector information is provided by crossing the two technology classes with the export status. Some of the main firm characteristics of interest for this paper are considered: the TFP level, the capital-labor ratio, and the size as proxied by the number of permanent employees. Across the two technology classes, marked differences are evidenced. It is worth mentioning that both exporters and non-exporters share the two empirical technology classes. Large TFP differences are displayed between these classes except for Textiles. The percentage of exporters which are likely to have adopted the Class 2 technology varies from 8.1% (Garments) to 14.8% (Food and Processing) and is found higher than for non-exporters. Textiles still remain the exception: 5.9% against 11.4%. The simple mean of this percentage over the five industries is, however, limited: 10% for exporters and 9.4%for non-exporters. This leads to the conclusion that the export status is not the most relevant criterion to discriminate firm technology choices in the Egyptian manufacturing sector.

A second conclusion deserves attention. Over the two technology classes, exporters tend to be both larger and more capitalistic. In addition, they have higher TFP levels, although this assertion has to be qualified for Garments (Class 2) and Metal (Class 1), where differences are not statistically significant. In Class 1, the productive performance is systematically related to a higher capital-labor ratio. In Class 2, this result is only found for Textiles, with a difference statistically significant at a confidence level of 99%. For Food and Chemical industries, the relation between TFP levels and the technological choice is impressive, approximately twice as high as in Class 2, but the average size of the firms is also different.

Table 5.Firm characteristics, export status, and technology

Sectors	Class 1 X	NX	t-test	Class 2 X	NX	t-test	Clas 1 X+NX	Clas 2 X+NX	t-test
Chemistry (563)	**(163)**	**(347)**		**(19)**	**(34)**		**(510)**	**(53)**	
TFP	4.3	3.8	***	15.3	6.0	***	4.0	9.3	***
K/L	44.3	25.9	***	22.4	17.5	Ns	31.7	19.2	**
L	289	77.3	***	521.5	203.9	***	140.6	318	***
Food (446)	**(115)**	**(272)**		**(20)**	**(39)**		**(387)**	**(59)**	
TFP	4.7	4.3	*	13.7	9.6	***	4.4	11	***
K/L	41.8	22.7	***	49.2	39.4	Ns	28.4	42.7	***
L	325.7	89.4	***	174.8	67.9	***	159.6	104.2	**
Garments (520)	**(114)**	**(380)**		**(10)**	**(16)**		**(494)**	**(26)**	
TFP	4.7	4.1	***	7.0	5.5	Ns	4.2	6.1	***
K/L	8.9	7.7	*	9.7	9.9	Ns	8.0	9.8	ns
L	230.8	30.7	***	345	21.3	***	76.8	145.8	***
Metal (746)	**(170)**	**(497)**		**(21)**	**(58)**		**(667)**	**(79)**	
TFP	2.9	2.9	Ns	4.9	3.9	***	2.9	4.2	***
K/L	31.5	25.9	**	21.2	18	Ns	27.4	18.8	**
L	234.2	54.2	***	181.2	83	**	100.1	109.1	ns
Textiles (758)	**(177)**	**(505)**		**(11)**	**(65)**		**(682)**	**(76)**	
TFP	4.7	4.1	***	6.0	4.2	***	4.3	4.4	ns
K/L	32.6	22.6	***	64.1	23.6	***	25.2	29.4	ns
L	353.3	102.7	***	213.2	140.7	Ns	167.8	151.2	ns

Note: TFP : Total Factor Productivity; K/L : capital-labor-ratio; L: Number of permanent employees. X: firms declaring to export; NX: non-exporting firms. Student t-test, level of confidence: * (90%) ** (95%) *** (99%), ns: not significant. Class 1, 2: technology classes.

4. Comparison of firm TFP levels across Egyptian industries

4.1. TFP determinants

Table 6 sheds some light on factors correlated with firm TFP levels. 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 alternatively by a dummy variable or the export intensity (in other words, the percentage of exported sales).The model controls for heterogeneity across sectors as well as the year of implementation of the survey by dummy variables. In the largest econometric specifications, the base line regression (models 1, 2, 5, and 6) is augmented with some covariates. As a robustness check, models 4 to 8 relax the methodological constraints characterizing the LCM. Indeed, these models provide alternative regressions results when we use a standard non-parametric measure of firm TFP levels. These non-parametric measures are obtained by the ratio of sales to the weighted average of inputs. Wages and intermediate consumptions are respectively considered for their relative contribution to sales, the capital-input getting the complement to unity. On the one hand, non-parametric measures are calculated restrictively under the constant returns to scale hypothesis. On the other hand, they are not affected by a potential endogeneity bias of inputs that would require the use of Olley and Pakes (1996) or Levinshon and Petrin (2003)'s methods. Although these two methods have been extensively used in the recent applied literature, not only are they unable to be implemented in the framework of the LCM we refer to, but they require a time dimension that we do not have in this empirical context.

Table 6. Firm log TFP measures and some correlates, 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 dummy	0.115 (8.35) †		0.105 (6.01)†		0.172 (7.31) †		0.153 (5.12) †	
Export intensity		0.002 (6.61) †		0.001 (4.11)†		0.018 (4.24) †		0.001 (1.96)**
Probability Class 2	0.515 (21.9) †	0.511 (21.5) †	0.520 (22.0) †	0.517 (21.9) †	1.242 (30.7) †	1.235 (30.3) †	1.25 (30.6) †	1.240 (30.3)†
Size			-0.08 (-1.46)	0.00 (-0.08)				
Website			0.011 (0.72)	0.018 (1.12)			0.029 (1.06)	0.047 (1.71)*
Industrial zone			0.067 (4.82) †	0.07 (5.03)†			0.0476 (1.98)**	0.039 (1.61)
Skilled workers			0.000 (0.60)	0.000 (0.06)			0.000 (0.72)	0.000 (0.59)
Overdraft facility			0.012 (0.59)	0.018 (0.93)			0.028 (0.81)	0.017 (0.50)
Foreign licence			0.039 (1.82)*	0.047 (2.20)**			0.066 (1.79)*	0.081 (2.20)**
Managerial experience			-0.002 (-3.62)†	-0.002 (-3.44)†			0.038 (1.68)*	0.001 (1.51)
Constant	1. 271 (72.9) †	1. 2687 (71.6)†	1.45 (34.1)†	1.450 (33.7)†	1.228 (41.0)†	1.232 (40.5)†	1.255 (17.1)†	1.27 (17.2)†
Numb Obs	3033	3032	2988	2987	3033	3032	2988	2987
R^2	0.30	0.30	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 licence; 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 enquiries.

In all the specifications of Table 6, both the technology and the export status are significantly correlated with TFPs. With respect to the technology, across the five sectors, results can be interpreted as follows: an increase of 10% of the probability to belong to Class 2 increases the average productivity gain by about 5%. Regarding exports, on average over the whole sample, being an exporter goes hand in hand with a TFP premium of about 10%. Substituting export intensity to the export binary variable does not improve correlations. We therefore reject the idea of an impact conditional upon the proportion of activities exposed to the external competition. Two reasons can be put forward to enlighten this result: (i) the export ratio is likely to be more volatile than the export status and (ii) export intensity can be subject to an error in measurement. The fact is that every manager provides only one answer per survey and has to refer to a limited number of intervals reflecting exporting shares.

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 performances in relation to initial characteristics promoting this status. To appraise and 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 from 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 first algorithm compares 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 limit of this method is that all firms are included in the matching, although good matches receive a heavier weight than poor ones. By the nearest neighbor method, every exporter is matched with one or *n* non-exporters, while the radius algorithm limits matches to only the nearest neighbors within the caliper. There is no simple rule of thumb to use in order to select the best algorithm for matching. All of them are asymptotically equivalent, but potentially different, especially for small samples. We have in this case, an empirical sample and therefore, the different matching methods are implemented as a robustness check to test the consistency of the findings.

PSM procedures have been considered to address the following questions. First, does TFP performance differ between exporting and non-exporting firms that share common characteristics? Second, given the technology, do exporters demonstrate higher productive performance, the most natural transmission channel supposedly being the technical efficiency level, which would increase due to the stimulation of external competition? Comparisons related to this question are only made within the Class 1 technology, where the number of observations is large enough.

Table 7. Firm TFP levels and export status, analysis of the bonus through the PSM method

	Obs	Mean TFP exporters	Mean TFP non-exporters	Statistical difference	t-test	Balancing test (p-value)
	Exporters versus non-exporters (full sample, Class1 and Class 2 technologies)					
Chemistry						
- Nearest Neighbor	181/373	5.44	4.11	32.4%	2.74***	0.48
- Radius	181/373	5.44	4.16	30.8%	2.87***	0.91
- Kernel	181/373	5.44	4.16	30.8%	2.85***	0.85
Food						
- Nearest Neighbor	131/302	6.08	5.10	19.2%	1.47	0.41
- Radius	131/302	6.08	5.42	12.2%	1.05	0.48
- Kernel	131/302	6.08	5.47	11.2%	0.97	0.55
Garments						
-Nearest Neighbor	120/394	4.94	4.08	21.1%	2.28**	0.87
- Radius	120/394	5.09	4.18	21.8%	2.64**	0.80
- Kernel	120/394	5.04	4.16	21.2%	2.52**	0.64
Metal						
-Nearest Neighbor	191/548	3.16	2.85	10.9%	2.34**	0.24
- Radius	191/548	3.16	2.89	9.3%	2.28**	0.85
-Kernel	191/548	3.16	2.90	9.0 %	2.21**	0.83
Textiles						
-Nearest Neighbor	186/562	4.74	3.92	20.9%	3.96***	0.08
- Radius	186/562	4.74	3.97	19.4%	4.13***	0.11
- Kernel	186/562	4.74	3.97	19.4%	4.14***	0.16
	Exporters versus non-exporters (Class 1 technology)					
Chemistry						
- Nearest Neighbor	162/342	4.15	3.62	14.6%	2.25**	0.27
- Radius	162/342	4.15	3.80	8.9%	1.63	0.73
- Kernel	162/342	4.15	3.79	9.5%	1.78*	0.58
Food						
-Nearest Neighbor	111/264	4.64	5.24	-11.5%	-1.46	0.35
- Radius	111/264	4.64	4.83	-03.9%	-0.63	0.53
- Kernel	111/264	4.64	4.87	-04.7%	-0.75	0.46

Garments						
-Nearest Neighbor	111/378	4.68	4.31	8.6%	0.98	0.05
- Radius	111/380	4.68	4.18	12.9%	1.90*	0.71
- Kernel	112/380	4.68	4.20	6.4%	1.70*	0.58
Metal						
-Nearest Neighbor	170/490	2.94	2.85	3.2%	0.76	0.10
- Radius	170/490	2.94	2.81	4.6%	1.29	0.53
- Kernel	179/490	2.94	2.81	4.6%	1.28	0.42
Textile						
-Nearest Neighbor	175/498	4.62	4.26	8.5%	1.68*	0.02
-Radius	175/498	4.62	4.02	14.9%	3.87***	0.78
-Kernel	175/498	4.62	4.06	13.8%	3.40***	0.60

Note: Comparisons of TFP performance between exporters and non-exporters are based on the PSM methods. Results are provided with three techniques: Nearest neighbour (1), Radius, and Kernel. The t-test provides information about statistical differences among groups of firms. In the last column, by the balancing test, we wonder whether covariates still discriminate firms after the matching procedure has been done.

Table 7 contains the most important information on exporters and non-exporters, including the TFP gaps and PSM test results. The last column on the right of the table 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 conclusive 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 7 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. Relative differences in TFP 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, where differences are not negligible but also not statistically significant, suggesting strong heterogeneity within this sector. In the lower part of Table 7, matching is restricted to firms of Class 1 technology. The number of observations attached to this class has the valuable advantage of being large enough to allow for comparisons for every manufacturing sector. The application of previous tests on the Class 2 technology is much more 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 potential impact from economies of scale or the difference between firm product prices due to heterogeneous qualities. TFP gaps are then much less convincing, 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, results are inconclusive, no matter which algorithm we consider.

5. Conclusion

Egypt has had a long history of state interventionism. Over several decades, public policies succeeded with the recurrent objective of promoting a diversified and sustainable industrial base to satisfy the need for job creation. From the “open door” policy of the 19070s to the end of the 1990s, most reforms proved only partially implemented with limited impact on structural change. Some substantial reorientations took place in the early 2000s with the official endorsement of a new pro-market strategy stimulating the development of manufactured exports. Attaining this goal required that firms improve their productivity, which has been traditionally regarded as low. The reflection underlying this paper has been focused on the analysis of the role of the export status and technology on TFPs. To take into account the heterogeneity of the technology, a finite mixture of productions functions (LCM) has been adopted. Firms are then allocated to a set of technologies and their respective productivity is determined.

Some broad conclusions have emerged from this analysis. A common technology for all firms has been statistically rejected for the five studied sectors. On the basis of the input elasticities of the LCM, each manufacturing sector is found to have both a labor-intensive technology (Class 1) and a capitalistic one (Class2). Exporters and non-exporters use both technologies and the choice of the most productive one is strongly correlated with firm TFPs. Whatever the adopted technology, exporting firms prove more productive, except for Metal (Class 1) and Garments (Class 2). Roughly speaking, the primary results still hold when pooling observations across the five sectors and TFPs are regressed on a vector of covariates. The technological impact is the prevailing correlate but the export status also matters, capturing a technical efficiency premium of about 10% over non-exporters. In order not to ignore the presence of a potential selection bias, the PSM method has also been used. Over the full sample, with some variations according to the sector as well as the technique of the matching we use, productivity levels are found to be in favour of exporters, except for Food, where differences across groups are not statistically significant. TFP gaps vary from about 9% (Metal) to 32% (Chemistry). When the sample is restricted to the labor-intensive technology (Class 1), TFP differences are less evident. Their magnitude is more or less 10% for three sectors (Chemistry, Textiles, and Garments), quite close to the result we get when a regression is run across the whole sample pooling all sectors, controlling for the technological impact, but without paying attention to the potential impact of the self-selection bias.

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 and Corral J.D (2010). Identifying different tecnhologies using a Latent Class Model/ extensive versus intensive dairy farms. *European Review of Agricultural Economics*, vol 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.

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? inFosu, 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: DoesBusiness 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.

Fafchamps, M., Hamine S. E. (2008).Learningto 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.

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 PaperNo 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,Vol 64, 6*, 1263-1297.

Orea, L.,&Kumbhakar, S. (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.

Roberts, M.,&TyboutJ. (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 ObservationalStudies 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 andtechnical 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, *Handbookof International Trade*, 388–415. Malden, MA: Blackwell Publishing.

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

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

Appendix 1

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

	Chemistry	Food	Garment	Metal	Textile
Log Labor	0.46 (7.99) †	0.29 (4.33) †	0.61 (5.00) †	0.43 (8.46) †	0.34 (7.74) †
Industrial zone	0.57 (4.07) †	0.55 (3.53) †	0.61 (2.78) †	0.25 (1.97) **	0.32 (2.60) †
Growth expectation	0.53 (3.63) †	0.42 (2.52)**	0.56 (2.90) †	0.51 (3.82) †	0.37 (2.97) †
Website	0.26 (1.71) *	0.72 (4.10) †	0.55 (2.54) **	0.39 (2.68) †	0.82 (6.33) †
Skilled Workers	0.04 (1.07)	0.00 (1.17)	0.00 (1.20)	0.00 (0.58)	0.00 (0.26)
Overdraft facility	0.43 (2.40)**	0.23 (1.09)	0.11 (0.36)	0.03 (0.16)	0.10 (0.60)
Foreign Licence	0.33 (1.87)*	0.08 (0.28)	1.11 (3.35) †	-0.00 (-0.01)	0.48 (2.65) †
Managerial experience	- 0.00 (- 0.61)	0.00 (0.21)	- 0.01 (- 0.85)	0.02 (3.92) †	0.01 (1.35)
Constant	-1.55 (-4.01)	-0.91 (-1.78)*	-1.58 (- 2.25)**	-2.60 (-7.20) †	-1.31 (-3.78)†
Nbobserv	554	433	514	739	748
Pseudo R^2	0.37	0.30	0.59	0.36	0.34

Appendix 2

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