Measuring Productivity: an Application to Moroccan Firms

Marion Dovis
Centre d'Economie et de Finances Internationales
Université de la Méditerranée - Aix-marseille II
Château La Farge – Route des Milles – 13290 LES MILLES AIX-EN-PROVENCE
e-mail : mariondov@aol.com

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Abstract

This paper analyses the productive performance in a set of 497 firms which represent seven manufacturing sectors of the Moroccan economy in 1998 and 1999 : chemicals, electrical, food, clothing, leather, plastics and textile. To appraise the productive performance, several models are used. The firm efficiency scores are derived from four type of models, the index numbers, the data envelopment analysis (DEA), the stochastic frontiers analysis and the Levinsohn and Petrin (2003) approach. The study uses the results in order to try to understand the possible determinants of productivity. At the beginning of the trade liberalisation, we found that the average domestic tariffs, the range of products, and the age of the capital are determinants of the efficiency of firms.

Keywords: DEA, Stochastic frontier, Technical efficiency, Trade.

JEL : D24, F14, O39.

I - Introduction

The idea of this paper is to focus on the process of trade liberalisation between the European Union (EU) and the countries of the Middle East and North Africa (MENA). The aim is to identify the possible impact of that process on firms. We focus this study on a set of 497 firms which represent seven manufacturing sectors of the Moroccan economy in 1998 and 1999 : chemicals, electrical, food, clothing, leather, plastics and textile.

The EU and the countries of the MENA have been engaged in a process of integration and trade liberalisation since 1995. This process have been called the Barcelona Declaration. Under this process each of the Mediterranean partner countries have signed Association Agreements with the EU. The important point of the agreements is the elimination of Mediterranean partner tariffs on EU exports. Moreover, there are protocols on issues such as technical assistance, improved access to EU markets, and rules of origin. The aim for these Mediterranean partners is to improve their economic growth and development, through closer links with the EU.

There is a well-established literature about the relationship between trade and economic growth. There is no consensus about this relation, but most economists tend to a positive relation between trade liberalisation and growth. There are lot of difficulties to identify this link, like finding satisfactory measures of openness and trade to identify the direction of the causality. However, this link is not sufficient to explain a higher growth rate. This will depend to a high degree on the underlying economic, institutional and indeed socio-political environment. Under the right conditions, more open economies are more likely to grow faster.

So, there are possible channels which could bring increases in overall productivity levels. Three key channels can be identified : the first concerns the inter-sectoral level, changes in trade policy are likely to lead to a reallocation of resources to sectors. The second is the intra-sectoral level, here the changes take place within a given sector. And the third is the changes in firm-level productivity, the channel is through existing firms increasing their levels of productivity. It is important to shed light on those policies that may be more likely to stimulate higher rates of economic growth. The three channels identified above, as well as the more detailed mechanisms driving changes in firm level productivity are all possible and plausible. We have little information and evidence on which channels and mechanisms are in reality more important, or under which circumstances they are more likely to play an important role. Many of the identified mechanisms imply heterogeneity at the firm level.

Much of what is captured under the intra-sectoral level and the firm level occurs in a framework where firms are non-homogeneous units. It therefore follows, that in order to address these questions it is important to work with firm level data.

The frontier approach to total factor productivity measurement makes possible to distinguish between shifts in technology from movements towards the best practice frontier. By estimating the best practice production function (an unobservable function) this approach calculates technical efficiency as the distance between the frontier and the observed output. Two different techniques have been used to measure technical efficiency under the frontier approach, which differ in the assumptions imposed on the data. There are parametric techniques and non parametric techniques. In this paper we choose the Data Envelopment Analysis (DEA) for the non parametric model and the stochastic frontier analysis (SFA) for the parametric model. Due to the simultaneity bias, we also perform the Levinsohn and Petrin (2003) approach. And in order to complete this study, we include the index numbers approach with the Fisher, Törnqvist and Malmquist index.

The relative strengths and weaknesses of these approaches have been vigorously debated, and will continue to be. That way, technical inefficiency scores obtained by estimating the different models and rank correlation are also compared.

So, the structure of this paper is as follows: in the section 2 we briefly explain the different models of productivity estimates and the explanatory variables involved in the empirical study. The empirical results are presented and discussed in the section 3. And we find and conclude in section 4, that average domestic tariffs, the range of the product and the age of capital are determinants of the technical efficiency of these firms.

II – Model specifications and data sources

In general there are two possible techniques available for estimating a measure of productivity at firm level, parametric and non-parametric. The non-parametric approaches involve either the index number approach or Data Envelopment Analysis (DEA).

2.1 - Non-parametric approach :

- The index numbers:

The index number approach derives directly from the growth accounting framework. It provides a theoretically motivated aggregation method for inputs and outputs. In general, we can define the index number as a real number which measure changes in a set of linked variables.

- The Fisher and the Törnqvist index:

The choice is difficult through the variety of index numbers. Most studies concerning this subject use a set of properties that index numbers have to satisfy. For Caves, Christensen and Diewert (1982a), the Fisher index and the Törnqvist index are the most interesting. Diewert (1992) also find that the Fisher index is efficient. Although these are old models, they are widely used.

The Fisher (1922) index is represented by

$$Q^F = \sqrt{\frac{\sum_{i=1}^{N} p_{i0} q_{i1}}{\sum_{i=1}^{N} p_{i0} q_{i0}} \cdot \frac{\sum_{i=1}^{N} p_{i1} q_{i1}}{\sum_{i=1}^{N} p_{i1} q_{i0}}} \qquad (1)$$

where respectively, p_{it} and q_{it}, represent the price and the quantity of the product i (i=1,2, …,N) at time t (t=0,1).

Törnqvist (1936) indices are weighted geometric averages of growth rates for the economic data. It is the formula of the natural logarithm of a Törnqvist index that is usually shown. For the output quantity index, this is

$$\ln Q^T = \frac{1}{2} \sum_{i=1}^{N} \left[\left(p_{i0} q_{i0} \Big/ \sum_{i=1}^{N} p_{i0} q_{i0} \right) + \left(p_{i1} q_{i1} \Big/ \sum_{i=1}^{N} p_{i1} q_{i1} \right) \right] [\ln q_{i1} - \ln q_{i0}] \qquad (2)$$

However a possible disadvantage is that the index assumes constant returns to scale and perfect competition in both input and output markets. But these indices require minimum data.

- The Malmquist index :

Caves, Christensen and Diewert (1982a) extended the index number approach, allowing for technical change that is not Hicks-neutral and variable returns to scale. They start from the

Malmquist (1953) productivity index and represent the technology by output and input distance functions.

The Malmquist productivity index is defined by using distance functions. Distance functions allow one to describe a multi-input, multi-output production technology without the need to specify a behavioural objective. There are two types of distance function, the input distance function and the output distance function. An input distance function characterises the production technology by looking at a minimal proportional contraction of the input vector, given an output vector. An output distance function considers a maximal proportional expansion of the output vector, given an input vector. In this paper we only explain an output distance function in detail.

A production technology may be defined using the output set, $P(x)$, which represents the set of all output vectors, y, which can be produced by using the input vector, x. That is,

$$P(x) = \{y : \text{x can produce y}\}$$

The output distance function is defined on the output set :

$$d_o(x, y) = \min\{\delta : (y/\delta) \in P(x)\}$$

The distance function , $d_o(x, y)$, will take a value which is less than or equal to one if the output vector, y, is an element of the feasible production set, $P(x)$. Moreover, the distance function will take a greater value than one if y is located outside the feasible production set.

The Malmquist total factor productivity (TFP) index measures the changes in TFP between two points, by calculating the ratio of the distances of each data point relative to a common technology. According to Caves, Christensen and Diewert (1982b) the Malmquist (output-orientated) TFP change index between period *t* (the base period) and *t*+1 is given by

$$m_o^t(y_t, y_{t+1}, x_t, x_{t+1}) = \frac{d_o^t(y_{t+1}, x_{t+1})}{d_o^t(y_t, x_t)} \qquad (3)$$

where the notation $d_o^t(x_{t+1}, y_{t+1})$ represents the distance from the period *t*+1 observation to the period *t* technology.

Thus Färe, Grosskopf, Norris et Zhang (1994) extend this approach by defining the Malmquist TFP index like a geometric mean of two TFP indices.

$$m_o(y_t, x_t, y_{t+1}, x_{t+1}) = \left[\frac{d_o^t(y_{t+1}, x_{t+1})}{d_o^t(y_t, x_t)} \times \frac{d_o^{t+1}(y_{t+1}, x_{t+1})}{d_o^{t+1}(y_t, x_t)}\right]^{\frac{1}{2}} \qquad (4)$$

An equivalent way of writing this productivity index is:

$$m_o\left(y_t, x_t, y_{t+1}, x_{t+1}\right)=\frac{d_o^{t+1}\left(y_{t+1}, x_{t+1}\right)}{d_o^t\left(y_t, x_t\right)}\left[\frac{d_o^t\left(y_{t+1}, x_{t+1}\right)}{d_o^{t+1}\left(y_{t+1}, x_{t+1}\right)}\times\frac{d_o^t\left(y_t, x_t\right)}{d_o^{t+1}\left(y_t, x_t\right)}\right]^{\frac{1}{2}} \qquad (5)$$

where the first ratio measures the technical efficiency between the two period and the second term technical changes.

- The Data Envelopment Analysis:

The DEA is non-parametric and requires linear programming, which uses data on the inputs and outputs quantities of a group of firms to construct a piece-wise linear surface over the most efficient observations. This surface is constructed by the solution of a sequence of linear programming problems, one for each firm in the sample. So, this method identifies the firms that make the most efficient use of inputs to produce outputs.

The method dates back to Farell (1957) who introduced the idea of production efficiency decomposed in two part, the technical efficiency and the allocation efficiency. These two measures represent the total efficiency. The term of Data Envelopment Analysis was first introduced by Charnes, Cooper and Rhodes (1978) who proposed an input orientated model with constant returns to scale.

The DEA can be either input orientated or output orientated. This means that it identifies those firms that use the least amount of input while producing a given amount of output (input orientation) or, at the opposite, produce the greatest amount of output for a given amount of input (output orientation).

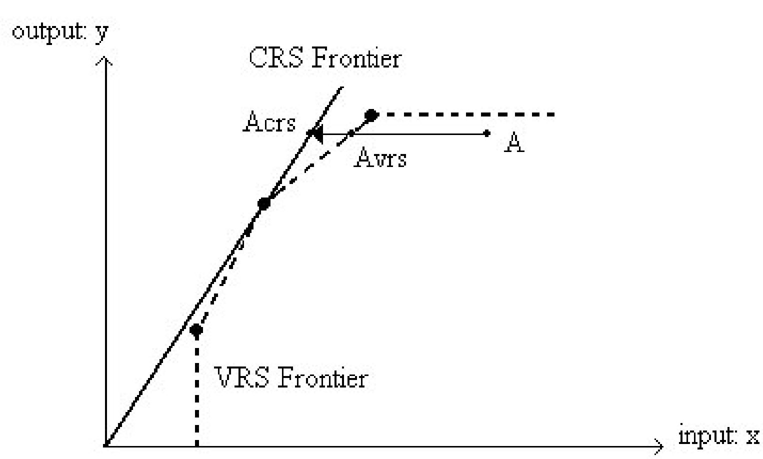

Figure 1 : The returns to scale in DEA model

If the technology is restricted to constant returns to scale, the frontier is forced to go through the origin and is extrapolated beyond observed points.

If one has data for N firms, the linear programming problem that is solved for the I-th firm in an output-orientated DEA model is as follows:

$$\begin{aligned} &\max_{\phi,\lambda} \phi, \\ &\text{s.t.} \quad -\phi y_i + Y\lambda \geq 0, \\ &\qquad x_i - X\lambda \geq 0, \\ &\qquad \lambda \geq 0, \end{aligned} \tag{6}$$

where X is a (N×K) matrix of input quantities of all firms, and Y is a (N×M) matrix of output quantities of all firms. Consequently, x_i is a (K×1) matrix of input quantities for the I-th firm, and y_i is a (M×1) matrix of output for the I-th firm. λ is a (N×1) vector of weights and θ a scalar.

With $1 \leq \phi$, and $\phi - 1$ is the proportional increase in outputs that could be achieved by the I-th firm. Note also that $1/\phi$ define a technical efficiency score, in a output orientation with constant returns to scale, which varies between zero and one. This linear programming problem can be easily modified to take for variable returns to scale into account by adding the convexity constraint: $N1'\lambda = 1$, where N1 is an (N×1) vector of ones.

DEA has some advantage like to deal with many outputs in a consistent way. The surface does not rely on any restriction on the functional form of the production function. Nevertheless, there are limitations, measurement error and other noise may influence the shape and the position of the frontier. The outliers may influence the results. And the omission of an important input or output may bias the results.

2.2 – Parametric method :

- The Stochastic Frontier Analysis:

The overall idea of stochastic frontier models is the use of assumptions on the distribution of a unobserved productivity component to separate productivity from the deterministic part of the production function and the random error.

Stochastic frontier analysis was originally due to Aigner, Lovell et Schmidt (1977) and Meeusen and van den Broeck (1977). These models were based on cross sectional data and strong distributional assumptions. Similar model have also been developed for panel data.

The basic model that we consider is as follows:

$$\ln(y_i) = x_i\beta + v_i - u_i, \qquad \text{i} = 1, 2, ..., \text{N}. \qquad (7)$$

where N is the total number of firms, $\ln(y_i)$ is the logarithm of output for the I-th firm, x_i is a vector of inputs quantities for the I-th firm. β is a vector of unknown parameters. The v_i term is distributed as $N(0, \sigma_V^2)$, in which σ_V^2 stands for the variance of stochastic disturbance v_i. The u_i term is a non-negative random variable that captures the unobservable inefficiency effect. Distributed independently from and identically to v_i, and has distribution equal to the upper half of the $N(0, \sigma_u^2)$ distribution. Estimation is usually made with maximum likelihood.

This last assumption implies that the u_i are half-normal, but this could be replaced by another specific distributional assumption, as in Stevenson (1980). He introduced a truncated normal distribution that is more flexible on the location of the mode of the distribution. There are no a priori reason for choosing one distributional form over the other, and all have advantages and disavandtages (Coelli, Rao and Battese, 1998).

More specifically, the technical efficiency of the I-th firm is $TE_i = \exp(-u_i)$. The calculation of the γ parameter shows the importance of the inefficiency term in explaining the total residual variance denoted $(\sigma_u^2 + \sigma_v^2)$: $\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$, with $0 \le \gamma \le 1$. If γ tends to one, it means that the residual of the regression expresses the inefficiency term.

This approach assumes that the input trade-off and returns to scale are the same for all observations. All firm heterogeneity is concentrated in the productivity term.

Estimation of stochastic frontier analysis requires a particular functional form of the production function to be imposed. A range of functional forms for the production function frontier is available. We use the most frequently used. Firstly, a translog function , which is a second order linear form. This is a relatively flexible functional form, because it does not impose assumptions about constant elasticities of production nor elasticities of substitution between inputs. It thus allows the data to indicate the actual curvature of the function, rather than imposing a priori assumptions. In general, this can be expressed as:

$$\ln Y_i = \beta_0 + j\sum_i \beta_j \ln X_{j,i} + \sum_j \sum_k \beta_{j,k} \ln X_{j,i} \ln X_{k,i} + v_i - u_i \qquad (8)$$

Where, the subscripts *I* represents the I-th firm.

Secondly, the Cobb-Douglas case, this production function imposes more stringent assumptions on the data than the translog function, because the elasticity of substitution has a constant value of one. And the elasticity of substitution is constant for all inputs. The Cobb-Douglas production function is given by:

$$\ln Y_i = \beta_0 + \sum_j \beta_j \ln X_{j,i} + v_i - u_i \qquad (9)$$

Note that some exogenous variables may influence the productive efficiency with which inputs are converted into outputs. This variables potentially explain difference across firms. So, in this study we assume that u_i is distributed as $N\left(m_i, \sigma_u^2\right)$ and is truncated at zero from above, where the mean is defined by

$$m_i = z_i \delta \qquad (10)$$

where, m_i is a vector of state specific effects, with z_i a vector of variables which may influence the efficiency of state and δ a vector parameter to be estimated.

Following Battese and Coelli (1993) maximum likelihood estimation (performing using FRONTIER 4.1, Coelli) is employed to simultaneously estimate the parameters of the stochastic frontier and the technical inefficiency effects model. The results of this procedure are represented in Table 3.

- The semi parametric approach of Levinsohn and Petrin (2003):

Consistent estimation of the input parameters faces an endogeneity problem, first discussed by Marschak and Andrews (1944). The problem is that firms choose inputs knowing their own level of productivity.

This model is in turn based on the work of Olley and Pakes (1996). To overcome this problem, the idea of Olley and Pakes is to use the investment as a proxy for the unobserved productivity shocks. Levinsohn and Petrin (2003, L&P) suggest that investment is not a continuous variable plants and it may not respond fully to productivity shocks. They therefore proposed electricity usage as a proxy. Just note that, in order to identify the capital and the productivity coefficients panel data is required.

Under this approach the production technology is assumed to be Cobb-Douglas:

$$y_t = \beta_0 + \beta_l l_t + \beta_k k_t + \beta_m m_t + \omega_t + \eta_t \qquad (11)$$

where y_t is the logarithm of the firm's output, l_t and m_t are the logarithm of the freely variable inputs labour and the intermediate input, and k_t is the logarithm of the state of variable capital.

The error as two components, the transmitted productivity component given as ω_t, and η_t, an error term that is uncorrelated with input choices. The intermediate input's demand function is given as

$$m_t = m_t(k_t, \omega_t) \qquad (12)$$

Levinsohn and Petrin show that the demand function is monotonically increasing in ω_t. This permit

$$\omega_t = \omega_t(k_t, m_t) \qquad (13)$$

So, the production function can now be expressed

$$y_t = \beta_l l_t + \phi_t(k_t, m_t) + \eta_t \qquad (14)$$

where

$$\phi_t(k_t, m_t) = \beta_0 + \beta_k k_t + \omega_t(k_t, m_t) \qquad (15)$$

Then we can approximate the unknown function, ϕ_t, by a third order polynomial in k_t and m_t. In the first stage, β_l and ϕ_t are estimated and the second stage of the routine identifies the coefficient β_k where productivity is assumed to evolve according to a first-order Markov process.

2.3 – Data :

The data for our study derive from a detailed firm level survey (Firms Analysis and Competitiveness Survey, FACS) carried out jointly by the World bank and the Ministry of trade and industry. The survey covers 859 enterprises and contains data for seven sectors for

1998 and 1999[1]. The seven sectors covered are: chemicals, electrical, food, clothing, leather, plastics and textile. The survey is based on firms with more than 10 employees.

The interest of this survey is that it contains extremely detailed information at the firm level. We have information on the sales of each of the three principal products produced by the firm. We also have detailed information on labour supply and training within each firm, the use of intermediates both imported and domestically supplied, as well as a range of information concerning the underlying financial structure of each firm, the institutional environment within which it operates, as well as the view of the firm concerning issues such as trade barriers, degree of competition for its products etc. In contrast the key disadvantage of this data set is that the data is for two years only. This involves a work on cross-section and no panel estimation, and this means that we have to focus on the third channel.

Moroccan industry is divided into 18 sectors, which are listed in Table 1. In 2000 the 18 manufacturing sectors of the Moroccan economy comprised a total of 6652 firms 63% of which (4124) were firms with more than 10 employees, 2278 of which were in the FACS industries.

Table 1 – Sectoral shares in Employment, VA and Exports, 1999

Sector	**Emp.**	**VA**	**Exports**
Food industry	5.6	**11.1**	0.3
Other Food ind.	**12.8**	**16.0**	**20.1**
Beverages and Tobacco	2.3	8.1	0.2
Textiles & hosiery	**13.4**	6.9	**12.7**
Clothing	**26.2**	6.5	**24.4**
Leather	3.1	1.3	3.6
Wood	2.2	2.0	1.2
Paper & cardboard, printing	3.3	4.4	1.3
Mineral related materials	8.0	7.4	1.0
Primary metallic industry	0.4	1.3	1.1
Metal working machinery	5.3	6.2	1.2
Machinary & equipment	1.4	1.1	0.1
Transport equipment	2.9	4.7	4.8
Electrical and electronic appliance	3.1	2.9	2.8
Office equipment & instruments	0.2	0.2	0.1
Chemistry	6.8	**17.2**	**23.9**
Rubber or *plastics*	2.8	2.4	1.2
Other manufacturing Indus.	0.1	0.1	0.0

[1] The survey also contains some data for 1997 but only for certain variables.

In this study, we use the data on value added for the output. It is calculated as the difference between total production and intermediate consumption. For the input capital, we use the sum of buildings and tools after depreciation, which is obtained from the balance sheet of the firms. And the labour input is represented by the wage and social charges. Naturally, these variables are logged for the stochastic frontier analysis. And concerning the z variables, we use the localization of the firms and dummies for the sectors. Because of the lack of data for some firms we estimate the technical efficiency for 497 firms.

III - Estimation results

3.1 - Estimations for the entire sample :

Firstly, we compare the results of the different methodology in the entire sample of 497 firms. Because of restricted data on consecutive years, we cannot evaluate all the models. The absence of more periods does not allow for a panel estimation of the stochastic frontier model. So, we estimate productivity in cross section.

With the flexibility of the DEA model, we can estimate the efficiency scores with the assumption of constant returns to scale or the assumption of variable returns to scale. Moreover, as we have seen before we can have an input orientation or an output orientation. The two measures provide the same technical efficiency scores when a constant returns to scale (CRS) technology applies, but are unequal when variable returns to scale (VRS) is assumed. In this paper we estimate these three possibilities, in order to know the differences.

Concerning the stochastic frontier model, we improve the model for the two assumptions on the production function, for the Cobb-Douglas case and the Translog case. We have hence decided to be selective in what results we present in this paper. We provide, in Table 2, information on the minimum and maximum efficiency scores, mean, variance and standard deviation of the two frontier techniques. We also provide information on the parameter estimates of the stochastic frontier models and the L&P model in Table 3.

Table 2 – Descriptive statistics of the efficiency scores

Model		Minimum	Maximum	Mean	Variance	Standard deviation
DEA CRS	1998	0,01200	1,00000	0,26871	0,02566	0,16019
	1999	0,00900	1,00000	0,26986	0,02514	0,15854
DEA VRS I	1998	0,02800	1,00000	0,33605	0,03842	0,19599
	1999	0,03100	1,00000	0,33501	0,03395	0,18427
DEA VRS O	1998	0,01500	1,00000	0,31115	0,03586	0,18936
	1999	0,00900	1,00000	0,31486	0,03324	0,18233
Cobb-Douglas	1998	0,05637	0,93881	0,74591	0,02183	0,14775
	1999	0,02979	0,94370	0,73424	0,02434	0,15600
Translog	1998	0,05428	0,93832	0,74439	0,02244	0,14979
	1999	0,02962	0,94371	0,73297	0,02490	0,15781

According to the results, the different method do not seem to have the same tendency. The mean efficiency levels do not evolve in the same way, they increase between 1998 and 1999 for the DEA model with CRS and for the output orientated in VRS whereas they decrease for the others. The efficiency levels are not located in the same interval, the DEA models have a mean efficiency between 0,265 and 0,340, and the stochastic frontier models have a mean efficiency between 0,730 and 0,750. Only variance and standard deviation are located in approximately the same interval.

Given that we have observations on 497 firms, we have a large computer output to describe for the DEA model. We have information on efficiency scores and peers of each firms. Hence, we do not describe futher the DEA results. Note that the average technical efficiency score of 0,270 in 1998 for CRS case implies that these firms are, on average, producing 27 percent of the output that could be potentially produced using the observed input quantities.

Concerning the SFA, we provide information in Table 3 for the coefficients of the parameter for the two estimations. In the Cobb-Douglas case, a total of 9 coefficients out of 11 are significantly different from zero. For the Translog production function, a total of 9 coefficients out of 14 are significant. For the inefficiency model, in the two cases, the food sector and the plastics sector are insignificant. In the two cases, the labour appears to be the most important input. The indicator of returns to scale is the sum of the coefficients of the inputs, which is 0,9914 for the Cobb-Douglas production function and 0,8944 for the Translog. This suggest CRS for the Cobb-Douglas case. In order to explain the interpretation of efficiency scores in the stochastic frontier model, just note that in the Cobb-Douglas case the mean efficiency scores is 0,734 in 1999. This indicates that the production level can increase on average by 26,6 percent. In principle, the SFA is biased because of the problem of the simultaneity between the choice of inputs and the firms' productivity. Interestingly, the L&P approach suggests higher coefficients for capital and labour.

For the index number estimations, they reveal that the mean efficiency of the firms during 1998 and 1999 increases by 1.1673 and 1.1679 for the Fisher and the Törnqvist index. Regarding the Malmquist index, it indicates an increase of 1.2048 for the entire sample. It is necessary to be careful on the conclusion due to the absence of a long time series.

Table 3 – Comparison of parametric results

Variable	Parameter	Translog Estimate	Translog t-ratio	Cobb-Douglas Estimate	Cobb-Douglas t-ratio	L&P Estimate	L&P t-ratio
Stochastic frontier model :							
Constant	β_0	1.1966	2.52	0.8272	7.26		
Ln(L)	β_1	0.4662	2.95	0.7887	34.10	0.833	26.14
Ln(K)	β_2	0.4211	3.74	0.2027	10.06	0.255	3.05
Ln(L)²	β_3	0.0320	1.51				
Ln(K)²	β_4	-0.0039	-0.25				
Ln(L)×ln(K)	β_5	-0.0210	-0.67				
Inefficiency model :							
Constant	δ_0	-14.5720	-3.41	14.9553	3.80		
Localization	δ_1	0.6544	3.64	0.6546	4.01		
Chemicals	δ_2	-2.3625	-2.24	2.2345	2.23		
Food	δ_3	1.4254	1.33	1.2892	1.23		
Clothing	δ_4	3.3757	3.20	3.4258	3.74		
Leather	δ_5	7.3824	3.46	7.7529	3.77		
Plastics	δ_6	0.1032	0.13	-0.4811	-0.55		
Textile	δ_7	4.9911	3.34	4.8954	3.86		
Variance parameter :							
	σ^2	4.0237	4.00	4.1513	4.34		
	γ	0.9744	131.79	0.9742	139.88		
Log(likelihood) :		-342.28		-340.04			

In Table 4 we provide correlations of the results across the different methodologies used. What emerges from the table is that there is a high degree of correlation across the two stochastic frontier methods employed, and a fairly high degree of correlation between the three DEA approach. Across the stochastic frontier and the DEA methodologies the correlation is lower. Concerning the L&P approach, this suggests differences across the results.

Table 4 - Correlation of productivity estimates across methodologies

		Non parametric			Parametric		
		CRS	**VRS I**	**VRS O**	**Cobb-Douglas**	**Translog**	**L&P**
Non param.	**CRS**	1					
	VRS I	0.8392	1				
	VRS O	0.9174	0.8691	1			
Param.	**Cobb-Douglas**	0.8288	0.6906	0.7996	1		
	Translog	0.8057	0.6544	0.7741	0.9852	1	
	L&P	0.4558	0.4908	0.4431	0.4628	0.4633	1

3.2 - Estimations by sectors

In this section, we run the regressions separately for each industry. This can allow to identify the outputs which are produced with the best efficiency by sector. The idea is to take the three most productive firms and describe their products, Table 6.

Concerning the evolution of the mean efficiency of the sectors, the plastics and the chemical sector have the best increase in their efficiency. The evolution of the electrical, leather and textile sectors, is lower.

Table 5 – Average index number by sector

Sector	Fisher Index	Törnqvist Index	Malmquist Index
Chemicals	1,3835	1,3834	1,3458
Electrical	0,9447	0,9446	1,0577
Food	1,1200	1,1200	1,2009
Garment	1,1674	1,1684	1,2220
Leather	1,0192	1,0206	1,0595
Plastics	1,7188	1,7202	1,6990
Textile	1,0238	1,0239	1,0480

Table 6 – The efficiency firms by sector

Sector	Position number	First product	Duty	Export share	First year production	First year exportation	Second product	Duty	Export share	First year production	First year exportation
Chemicals	1.	Photographs development	2.5%	0%	1992		Printing photographs	2.5%	0%	1992	
	2.	Insecticide	41.7%	5%	1961	1961					
	3.	Brilliantine	50%	0%	1968		Hair spray	50%	0%	1968	
Electrical	1.	Electric water heater	26.3%	0%	1978						
	2.	Power cord	37.5%	100%	1990	1990					
	3.	Circuit breaker	40%	40%	1976	1981	Power cord	43.3%	40%	1976	1981
Food	1.	Roasted coffee	50%	0%	1924						
	2.	Pressed yeast	40%	0%	1977		Dry yeast	40%	0%	1980	
	3.	Coffee	32.5%	0%	1966						
Clothing	1.	Tee shirt	50%	100%	1989	1989	Trouser	50%	100%	1998	1998
	2.	Trouser	50%	100%	1988	1988	Jacket	50%	80%	1988	1988
	3.	Shirt	50%	100%	1991	1991	Trouser	50%	100%	1991	1991
Leather	1.	Shoes	50%	100%	1992	1992					
	2.	Shoes	50%	100%	1992	1992					
	3.	Glove	50%	100%	1992	1992	Shoelace	50%	100%	1992	1992
Plastics	1.	Plastic bag	50%	0%	1980						
	2.	Polystyrene sheets	50%	0%	1975						
	3.	Cassette	23.3%	13%	1995	1995					
Textile	1.	Shoulder strap	50%	40%	1962	1975					
	2.	Cloth	37.5%	0%	1982						
	3.	Carpet	50%	0%	1980		Cloth	50%	0%	1980	

Sector	Position number	Third product	Duty	Export share	First year production	First year exportation		Total number of perceived competitors	Share of foreign capital	Share of imported raw materials	Share of product include in other production
	1.							120	0%	nc	0%
Chemicals	2.							15	99%	100%	0%
	3.	Shampoo	50%	0%	1968			10	0%	nc	0%
	1.							nc	10%	35%	60%
Electrical	2.							1	95%	100%	0%
	3.	Socket	32.5%	40%	1976	1981		3	0%	100%	0%
	1.							45	0%	100%	0%
Food	2.	Dry yeast SPI	40%	100%	1995	1995		1	77%	nc	0%
	3.							40	50%	100%	0%
	1.	Dress	50%	100%	1998	1998		700	12%	nc	0%
Clothing	2.	Dress	50%	80%	1988	1988		100	0%	75%	0%
	3.	Waistcoat	50%	100%	1991	1991		100	0%	nc	0%
	1.							50	0%	5%	10%
Leather	2.							nc	100%	100%	0%
	3.							30	55%	100%	0%
	1.							100	0%	100%	0%
Plastics	2.							3	0%	100%	0%
	3.							4	0%	100%	0%
	1.							1	0%	80%	0%
Textile	2.							40	99%	nc	0%
	3.							nc	0%	80%	0%

We can see that approximately more than 40 percent of these firms produce more than one output. And for the clothing industry, all of the more efficient firms produce three outputs.

The half of these firms exports their products. The three most efficient firms of the clothing and the leather sectors are based on an export strategy. All of their production is devoted to the export market and they systematically export the first year of production. In contrast almost all of the most efficient firms of the chemicals, the food, the plastic and the textile sectors do not export. The firms of the electrical sector are located between these situations. In the sum, when these firms decide to export they enter in this market very shortly after the first year of production. For a big part of them they enter the same year. Except for the leather sector, the majority of the firms produce their outputs for a long time.

Concerning the characteristics of these firms, we can note that the firms with foreign capital are 43 percent whereas the firms of the entire sample are only 22.5 percent. They import raw materials, 71 percent of them import raw materials among which 67 percent import all. And mostly of the products are not used for an other production.

IV – Concluding remarks and the link with trade

In this last section, we use the estimations of productivity of the entire sample in order to try and better understand the possible determinants of productivity. The underlying firm level data that we have from the FACS survey is very rich in firm level details. Hence the number of possible explanatory variables is quite interesting. We have focused on those variables which a priori one might expect to be important. We distinguish between those variables, which are related to productive system, quality of product, dynamics of the firm, institutional environment, international trade, and employment structure.

The results are given in Table 7, and here we focus on six sets of estimations based on six of the different productivity measures derived earlier. These are the DEA estimates in CRS, input-orientated VRS and output-orientated VRS, the stochastic frontier calculations with a Cobb-Douglas production function and a Translog production function, and the L&P approach. The first column of the table gives a brief description of the variables. Several of the variables are dummy variables where the firms were for example asked to respond yes or no[2]. We then present the coefficient estimates and the t-value of each of the variables for each type of productivity measures. And to facilitate interpretation for each variable we have calculated the marginal effect because we have dummy variables, some of the variables are shares and some are absolute values.

Hence, if we take the line of the results where we report on whether firms invest in R&D. Those firms that do R&D, are on average 10.4% more productive, when the estimation is based on the CRS DEA productivity measures. Where a variable is a share or percentage, then the marginal effect gives the percentage impact on productivity as a result of one percentage point increase in the variable. If we take the results for the share of capital which is between 5 and 10 years old. A 1% point increase results in an increase in productivity by 0.2%. Finally, there are variables in absolute values. These variables were logged and hence the coefficient on the variable gives the elasticity.

[2] Details of the variables are explained in the appendix.

Table 7 – The determinants of productivity

Variable	DEA CRS			DEA VRS I			DEA VRS O		
	Coef.	t-value	ME	Coef.	t-value	ME	Coef.	t-value	ME
Constant	-1.635**	-3.03		0.044	0.10		-1.667**	-3.11	
Productive system: capital < 5 years	-0.025	-0.23	0.0%	-0.126	-1.39	-0.1%	0.019	0.17	0.0%
capital 5 < 10 years	0.241**	2.39	0.2%	0.205**	2.48	0.2%	0.264**	2.64	0.2%
Quality of product: Range	-0.149**	-2.94	-16.1%	-0.055	-1.32	-5.6%	-0.147**	-2.90	-15.8%
ISO	-0.114	-1.34	-12.1%	-0.032	-0.46	-3.2%	-0.066	-0.78	-6.8%
Dynamic variables: R&D	0.099	0.99	10.4%	0.069	0.84	-7.1%	0.131	1.32	14.0%
Preparation for trade UE	0.044	0.71	4.5%	-0.027	-0.53	-2.7%	0.049	0.81	5.0%
MEDA funding applied for	0.112	0.59	11.8%	-0.049	-0.32	-5.0%	0.044	0.24	4.5%
Institutional var.: Fiscal facilities	-0.070	-0.96	-7.2%	-0.087	-1.45	-9.1%	-0.044	-0.61	-4.5%
Infrastructure	-0.131	-1.44	-14.0%	-0.138*	-1.83	-20.1%	-0.172*	-1.89	-18.8%
Ploughing back of profits	0.099	1.32	0.1%	0.117*	1.90	0.1%	0.089	1.19	0.1%
Trade variables: Foreign capital	-0.045	-0.51	0.0%	-0.069	-0.97	-0.1%	0.022	0.26	0.0%
Ave. dom. Tariffs	-0.431**	-2.25	-0.4%	-0.480**	-3.05	-0.5%	-0.367*	-1.93	-0.4%
Product export	0.245**	2.77	0.2%	0.029	0.40	0.0%	0.094	1.07	0.1%
Tariffs obstacle on X's	-0.054	-0.46	-5.5%	-0.063	-0.65	-6.5%	-0.047	-0.40	-4.8%
NTBs obstacles on X's	-0.056	-0.25	-5.7%	-0.171	-0.94	-18.6%	-0.209	-0.95	-23.2%
Employment struct. : Market share	0.222	1.40	0.2%	0.021	0.16	0.0%	0.288*	1.83	0.3%
Ave. length	0.084	1.53	0.1%	0.001	0.022	0.0%	0.079	1.45	0.1%
Ave. years of education	-0.108	-0.88	-0.1%	-0.240**	-2.35	-0.2%	-0.014	-0.12	0.0%
Skilled workers	0.671	1.54	0.7%	-0.396	-1.10	-0.4%	0.578	1.33	0.6%
Unskilled workers	0.747*	1.72	0.7%	-0.412	-1.16	-0.4%	0.599	1.39	0.6%
Employees out of production	1.069*	1.81	1.1%	-0.448	-0.92	-0.4%	0.808	1.38	0.8%
R^2			0.092			0.107			0.086

Variable	Cobb-Douglas			Translog			L&P		
	Coef.	t-value	ME	Coef.	t-value	ME	Coef.	t-value	ME
Constant	-0.847**	-2.72		-0.869**	-2.75		0.410	0.84	
Productive system:									
capital < 5 years	0.074	1.17	0.1%	0.076	1.17	0.1%	0.034	0.34	0.0%
capital 5 < 10 years	0.117**	2.01	0.1%	0.118**	2.00	0.1%	0.206**	2.26	0.2%
Quality of product:									
Range	-0.075**	-2.56	-7.8%	-0.079**	2.64	-8.2%	-0.081*	-1.76	-8.4%
ISO	-0.044	-0.89	-4.5%	-0.043	-0.87	-4.4%	-0.063	-0.81	-6.5%
Dynamic variables:									
R&D	0.067	1.16	6.9%	0.064	1.10	6.6%	0.039	0.43	4.0%
Preparation for trade UE	0.062*	1.75	6.4%	0.063*	1.74	6.5%	0.044	0.79	4.5%
MEDA funding applied for	0.106	0.97	11.2%	0.111	1.01	11.7%	0.105	0.62	11.1%
Institutional var.:									
Fiscal facilities	0.013	0.30	1.3%	0.019	0.44	1.9%	-0.062	-0.94	-6.4%
Infrastructure	-0.081	-1.54	-8.4%	-0.084	-1.57	-8.8%	-0.142*	-1.71	-15.2%
Ploughing back of profits	0.035	0.80	0.0%	0.035	0.80	0.0%	0.010	1.47	0.0%
Trade variables:									
Foreign capital	-0.025	-0.50	0.0%	-0.029	0.57	0.0%	-0.137*	-1.74	-0.1%
Ave. dom. Tariffs	-0.359**	-3.25	-0.3%	-0.359**	-3.20	-0.3%	- 0.577**	-3.34	-0.6%
Product export	0.049	0.96	0.0%	0.047	0.90	0.0%	0.117	1.47	0.1%
Tariffs obstacle on X's	-0.048	-0.71	-4.9%	-0.053	-0.77	-5.4%	-0.086	-0.81	-9.0%
NTBs obstacles on X's	-0.030	-0.23	-3.0%	-0.040	-0.31	-4.1%	-0.006	-0.03	-0.6%
Employment struct. :									
Market share	0.167*	1.83	0.2%	0.171*	1.84	0.2%	0.228	1.59	0.2%
Ave. length	0.026	0.82	0.0%	0.028	0.87	0.0%	0.032	0.64	0.0%
Ave. years of education	-0.003	-0.04	0.0%	-0.004	-0.06	0.0%	-0.177	-1.58	-0.2%
Skilled workers	0.668**	2.65	0.7%	0.689**	2.69	0.7%	-0.088	-0.22	-0.1%
Unskilled workers	0.731**	2.92	0.7%	0.754**	2.96	0.7%	-0.000	0.00	0.0%
Employees out of production	1.113**	3.27	1.1%	1.149**	3.32	1.1%	0.468	0.88	0.5%
R^2			0.112			0.113			0.082

** and *, significant at 5 and 10 percent.

If we now turn to the results, we notice that some variables are often significant. Some of them are very interesting. For the variables representing the productive system, the idea is to see if the different age of the capital plays a different role. Hence, the share of the capital between 5 and 10 years old is always significant and it has a positive influence on the efficiency of the firms. We can note that the coefficients of the share of capital younger than five years are low and insignificant. There is some evidence that when introducing new capital, there is a learning by doing process in using capital more efficiently.

Concerning the quality of the products, we have information on whether the firms' products are ISO certified or not and on the range of the product. The two variables have a negative impact and only the range is significant. We can see that the Moroccan firms are not efficient in the production of top of the range product. The firms that produce top of the range products are on average 7.8 percent to 16.1 percent (depending the productivity measure) less productive. This is an interesting result, which could have several interpretations. One possibility is that top of range products cannot lead to higher productivity. But we can also interpret this result as the fact that a top of range product provides quality which allows firms to impose higher prices.

The dynamic of the firms are represented by the effort in R&D, the preparation or not for the process of trade liberalisation with the EU, and the application for any MEDA funding. Only the preparation for the liberalisation appears significant at the 10 percent level for the two stochastic frontier models.

In the same way, the institutional variables do not seem to play an important role in productivity. Production problems represented by the infrastructure variable are likely to impact negatively on productivity and we would expect to find a negative coefficient. In all the different measures the coefficients are negative but only significant at the 10 percent level for the two DEA in VRS.

We next turn to looking at the role of the trade. The average domestic tariff represents the degree of domestic protection. We would expect a negative coefficient on the variable because in general high domestic tariff discourages the firms to be efficient. The different estimations indicate a negative and significant coefficient. A 1 percent point increase in the average domestic tariffs results in a decrease in productivity between 0.3 percent and 0.6 percent depending on the productivity measures. The share of export output is significant only for the DEA in CRS.

With the use of the foreign ownership variable, we are interested in exploring if through the introduction of foreign techniques and technologies the firms are more productive. But the foreign capital variable do not appear to be significant. For the variables of difficulties in exporting either due to high tariffs or to non-tariff barriers in export markets, the coefficients are negative. We might expect that high tariffs or non-tariff barriers discourage the firms to improve their productivity. But they are not significant.

In the last part, the employment structure, the share of skilled workers, unskilled workers and the share of employees out of production, are significant for the estimations with the stochastic frontier measures. Also for the measure of efficiency with DEA in CRS, the share of unskilled workers and employees out of production process are significant at 10 percent. All this variables have a positive link with the technical efficiency. Nevertheless, a 1 percent point increase in the share of employees out of production process has more influence on the increase of productivity (1.1 percent compared to 0.7 percent for the share of skilled workers and the share of unskilled workers). This involves an important point, a large part of skilled workers in a firm does not ensure a better productivity.

To resume, the determinants of the efficiency of the Moroccan firms are not necessarily those that we might expect to be important. And when the variables are significant they have little influence on the productivity.

The technical efficiency of firms determines its ability to transform input into a maximum of output. The differing economic behaviour shows the reasons why some firms increase their productive potential and others do not.

Our results indicate that inefficiency is present in production. Efficiency scores are obtained using non parametric and parametric models. The findings indicate that the choice of efficiency estimation method can make a significant difference in relation to average efficiency. DEA estimates are expected to be lower in general than econometric estimates. Accordingly, both estimation methods have been evaluated using the criteria rank correlation of efficiency scores. We show that the results of these estimations can differ, but the more efficient firms are the same for all the different measures.

With an application to sector samples, we note that a large part of the more efficient firms for each sectors product more than one goods, the half of them export their output, and a large part have foreign ownership and import their raw materials. Because there are characteristics of the economic and institutional environment that can represent a constraint for the firm efficiency, we try to understand the possible determinants of productivity. The results indicate that more productive firms tends to face lower domestic tariffs, use capital between 5 and 10 years old and have bottom of the range product.

Our economic analysis would benefit from more work to improve the comprehension of the determinants of the efficiency scores. However, in the aim to improve our estimations we need data on several years, more than two. The evolution of the productivity and the variables concerning the firm can enhance the explanation of the determinants.

Appendix

Data :

Concerning the regressions of the productivity measures, the variables are:

- Capital < 5 years : is the part of the capital low than 5 years old.
- Capital 5 < 10 years : is the part of the capital between 5 and 10 years old.
- Range : represents the range of the products (high range, middle range and low range).
- ISO : if the products are ISO certified.
- R&D : a dummy representing the investment in research and development.
- Preparation for trade union : the preparation or not for the process for trade liberalisation with the EU.
- MEDA funding : if MEDA funding applied for ?
- Fiscal facilities : a dummy representing fiscal facilities.
- Infrastructure : dummy for problem of infrastructures.
- Ploughing back of profits: the share of is own financing.
- Foreign capital : the share of foreign capital.
- Ave. dom. Tariffs : average domestic tariffs.
- Product exports : the part of the export output
- Tariffs obstacle on X's : dummy for the tariffs obstacle on exports.
- NTBs obstacle on X's : dummy for the non tariffs barriers obstacle on exports.
- Market share: the market share of the firm.
- Ave. length : average length of service.
- Av. years of education : average years of the education of the employees.
- Skilled workers : the share of the skilled workers.
- Unskilled workers : the share of unskilled workers.
- Employees out of production : the share of employees out of production.

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