ERF WORKING PAPER SERIES

EFFICIENCY MEASURE FROM DYNAMIC STOCHASTIC PRODUCTION FRONTIER: APPLICATION TO TUNISIAN TEXTILE, CLOTHING AND LEATHER INDUSTRIES

Rym Ben Ayed Mouelhi and Mohamed Goaied

Working Paper 0235

As of August 1998, financial support towards the ERF Working Papers Series from the Commission of the European Communities (through the FEMISE Program) is gratefully acknowledged. The views expressed in the Working Papers are those of the authors and do not necessarily reflect the views of the European Commission.

ECONOMIC RESEARCH FORUM

7 Boulos Hanna St. Dokki, Cairo, Egypt
Tel: (202) 3370810 – (202) 7485553 – (202) 7602882
Fax: (202) 7616042. Email: erf@idsc.net.eg. Website: http://www.erf.org.eg

Abstract

This paper is concerned with the estimation of firm and time-varying technical efficiency. The approach used to measure efficiency is different from the conventional static and stochastic frontier approach. We focus here on dynamic adjustment in attaining a target level of production. Technical inefficiency is modeled via an error correction type model. The main objective is to investigate the development of efficiency over time, the rate of technical change and the productivity growth. Estimation of a dynamic error components model is considered. The empirical analysis is based on an unbalanced panel data consisting of 388 firms from the Tunisian textile, clothing and leather industries (TCL) observed during 1983-1994. The mean efficiency score is found to be of 63 percent and there is no evidence of continuous increase in efficiency. We observe a technical regress during the period. We find that exporting firms are more efficient than the non-exporting ones and that the decline in efficiency is more pronounced for the non-exporting firms. Productivity growth rates are negative with a mean of –4 percent

1. Introduction

One of the most striking features of the economic environment of the past two decades has been the extension of policy reforms and trade liberalization in developing countries. The main reasons for the emphasis on trade liberalization are to accelerate growth and improve production efficiency.

These deep changes affect Tunisia, which since 1995 has adhered to free trade agreements with the European community. Henceforth, the productivity change and the technical efficiency of the textile clothing and leather (TCL) industries, which are essential for export, are one of the major issues confronting the Tunisian Economy.

The modeling and estimation of frontier production functions has been an important area of econometric research in the last two decades. The empirical results of the findings provide important guidelines for policy makers to better understand productivity differentials and the productive efficiency of firms.

The present study has two main goals. Our first motivation is to contribute to the development of studies of the behavior and performance of firms at the micro level in the TCL industries. The major empirical studies on industrial productivity in Tunisia suffer from aggregation bias, since they have been made at the macro or sectoral levels, and have been unable to capture the effects of heterogeneity of firms on productivity growth. In this study, we take advantage of information collected by the annual survey of firms in the TCL industries collected by the Institute of National Statistics in Tunisia.

Our second motivation is to apply econometric techniques from the dynamic panel data literature to evaluate firm and time-varying technical inefficiency. Thus the model does not carry the unreasonable implication that inefficiency is constant over time. The approach used to measure efficiency is different from the conventional static stochastic frontier approach. The static approach has two major shortcomings. First, the observed output need not necessarily be the optimal level. Second, the empirical analysis, being effectively non-dynamic, is unable to shed any light on the nature of dynamic output structure adjustment by firms. We focus here on dynamic adjustment in attaining a target level of production. Technical inefficiency is modeled via an error correction model type, which is more general than the partial adjustment type model used by Kumbhakar and al. (2000) in modeling efficiency in labor use. We allow any arbitrary pattern of temporal change. Technical efficiency is not confounded with individual specific-effects. In fact, since individual-specific effects also capture the effects of inputs that are invariant over time and such effects are not inefficiency, it is inappropriate to label the individual-specific effects as technical inefficiency. We don't assume a particular distribution for the effects. Productivity growth, technical change and adjustment speed are also studied in this paper. We define productivity growth as the net change in output due to change in efficiency and technical change, where the former is understood to be the change in how far an observation is from the frontier of technology and the latter is understood to be shifts in the production frontier.

A flexible translog function is used to represent the desired level of production, the maximum possible output for a given set of inputs. Firms adjust towards this frontier to catch up to the target level. Technical inefficiency is defined as the ratio of the desired production level given by the frontier to the observed one.

Estimation of the dynamic error components model is considered using an alternative to the standard first differenced GMM estimator (Arellano and Bond, 1991). It is a system GMM estimator deduced from a system of equations in first differences and in levels and exploiting extra moment restrictions (see Arellano and Bover, 1995 and Blundell and Bond, 1998a) for details). The system GMM estimator offers efficiency gains relative to the first differenced GMM estimator. Besides, it permits, in the context of production frontier issues, the identification of time-invariant variables if compared to the first differenced estimator. This makes it possible to control for possible differences in target output among firms of different characteristics.

The empirical analysis is based on an unbalanced panel data consisting of 388 firms from the Tunisian textile, clothing and leather industries (TCL) observed during 1983-1994. The static specification, which omits the delay of output adjustment, is considered and tested. Various statistical tests are undertaken to justify the validity of the moment conditions used and to evaluate the performance of the alternative specifications under study.

The paper is organized as follows. Section 2 contains the specification of a dynamic production function and the definition of inefficiency. Section 3 describes the data, reports and comments the estimation results. Section 4 concludes.

2. The Theoretical Model

To impose minimum restrictions on the technology, we approximate it by a flexible functional form, a translog production function, where for the representative firm i in period t:

$$\ln y_{it}^{*} = a_0 + a_1 \ln K_{it} + a_2 \ln L_{it} + a_{12} \ln K_{it} \ln L_{it} + a_{11} (\ln K_{it})^2 + a_{22} (\ln L_{it})^2 + \sum_t g_t D_t \qquad (1)$$

where y_{it}^{*} is the optimal output for firm i at time t, L and K are labor and capital inputs, D_t is a dummy variable having a value of one for the t^{th} time period and zero otherwise and the g_t are parameters to be estimated. The dummy variable D_t is introduced to model pure technology change according to the general index (GI) approach as suggested by Baltagi and Griffin (1988). This has the advantage of not imposing any structure on the behavior of technical change; it is capable of describing a complex behavior. This time dummy model allows for the time effects to switch from positive to negative and back to positive effects. The change in g_t between periods is a measure of the rate of technical change. This can be written as:

$$TC_{t,t+1} = g_{t+1} - g_t \qquad (2)$$

The optimal value y_{it}^* given by the equation (1) differs across firms and over time because of heterogeneity of firms and possibly shifts in the production frontier due to technical change.

Since the economy operates with some firms producing less than is technically possible at given levels of inputs, we label such firms as inefficient. A firm is said to be technically efficient if the observed production is equal to the optimal production for this firm. The output of firms that are not at their optimal level will be less than the maximum possible; we will refer to these firms as sub optimal firms. Technical inefficiency is then measured by the following ratio

$$EFF_{it} = \frac{y_{it}}{y_{it}^*} \qquad (3)$$

where y_{it} is the observed output. This ratio measures the degree of optimality of output of a firm. Since the optimal level itself may shift over time, a value of 1 at any time for this ratio does not have any implications for the future optimality of a firm. Firms are not necessarily efficient in every period but they adjust towards the production frontier and try to attain optimality. There is a catching up process modeled here as an error correction model which is more general than the partial adjustment model used by Kumbakhar and al. (2000) in modeling labor use efficiency. This error correction mechanism is specified (in logs) as

$$(\ln y_{it} - \ln y_{it-1}) = a(\ln y_{it}^* - \ln y_{it-1}^*) + b(\ln y_{it-1}^* - \ln y_{it-1}) \qquad (4)$$

or similarly

$$\ln y_{it} = (1-b)\ln y_{it-1} + a\ln y_{it}^* + (b-a)\ln y_{it-1}^* \qquad (5)$$

The parameters a and b reflect lags in adjustment of output to inputs. If $a = b$, then this dynamic behavioral equation is of the partial adjustment type. If $a = b = 1$, then the entire adjustment is made within one single period, but this is not always the case. If adjustments are costly, then firms may not find it optimal to adjust fully. In fact, whenever the workforce or the capital stock increases, it takes time for new workers or the new capital to become fully operational. Then, it takes some time for output to reach its new long-run level. This reflects the production consequences of the adjustment costs, which are associated with changes in factor inputs (Nickell, 1996 and Nickell-Wadhwani et Wall, 1992). If adjustment costs are not significant, then the specification is static, which corresponds to an instantaneous output adjustment.

Adding a composed random error to equation (5), we have

$$\ln y_{it} = (1-b)\ln y_{it-1} + a\ln y_{it}^* + (b-a)\ln y_{it-1}^* + a_i + v_{it} \qquad (6)$$

where a_i represents firm-specific effect which is not confounded here with inefficiency. Factors outside the control of firms are captured by appending a random error term v_{it}, the frontier is stochastic.

Equation (6) represents an equilibrium relationship given an adjustment cost. If observed output is simply regressed on inputs alone, then the inferred relationship suffers from misspecification Thus the production level depends on the production technology, technical inefficiency and also factors outside the control of firms, which are captured by the random variable v_{it}. Taking delays of adjustment into account is very important in measuring technical inefficiency. In fact, technical inefficiency is a measure of the discrepancy between a firm's actual output and its optimal output. This optimal level must be estimated from a dynamic specification in order to take into account delays of adjustment. If not, it is biased and so is the measure of inefficiency. To put it differently, omission of relevant variables (lagged dependent and inputs variables) may result in biased parameter estimates, which in turn produce biased, estimates of technical efficiency.

The long-term elasticities, for labor and capital respectively, can be derived as following

$$E_{y/L} = \frac{\partial \ln y_{it}^{*}}{\partial \ln L_{it}} = a_2 + 2a_{22} \ln L_{it} + a_{12} \ln K_{it} \quad (7)$$

$$E_{y/K} = \frac{\partial \ln y_{it}^{*}}{\partial \ln K_{it}} = a_1 + 2a_{11} \ln K_{it} + a_{12} \ln L_{it} \quad (8)$$

Efficiency change can be obtained from the change in the efficiency ratio expressed as

$$\dot{EFF} = \partial \ln EFF / \partial t = (\partial \ln y_{it} \ / \partial t - \partial \ln y_{it}^{*} / \partial t) \quad (9)$$

which decomposes the rate of change of output, or similarly the productivity growth $(\partial \ln y_{it} / \partial t)$, into efficiency change and technical change $(\partial \ln y_{it}^{*} / \partial t)$. Productivity growth is defined as the net change in output due to change in efficiency and technical change, where the former is understood to be the change in how far an observation is from the frontier of technology and the latter is understood to be shifts in the production frontier.

The production function defined by equation (6) will also be adjusted to account for relevant time invariant variables. That is, firm characteristics, like activity and whether or not the firm exports. By including firm type and activity, we control for possible differences in target output among firms of different characteristics.

We will estimate the dynamic model specified in equation (6) by GMM as suggested by Blundell and Bond (1998), without assuming any distribution for the error terms, taking into consideration the dynamic form and the presence of variables that are invariants over time. Estimation of the dynamic error component model is considered using an alternative to the standard first differenced GMM estimator of Arellano and Bond (1991). It is a system GMM estimator deduced from a system of equations in first differences and in levels. This estimator is defined under extra moment restrictions that are available under quite reasonable conditions relating to the properties of the initial condition process. Exploiting these extra moment restrictions offers efficiency gains and permits the identification of the effects of time invariant variables.

3. Data and Estimation Results

3.1 The Data

The data used in this study are taken from the national annual survey report on firms (NASRF) carried out by the Tunisian National Institute of Statistics (TNIS). The data covers nearly all firms for different industrial sectors (initially 5000) over the period 1983-1994. Although the data is collected by interviews, the Tunisian NASRF still suffers from a non-response mean rate of 57.5 percent for the period 1983-1988. Unfortunately, for the period 1989-1994, the TNIS does not report any information concerning both the non-response rate of firms and the reasons of non-response.

We will confine our interest to textile, clothing and leather (TCL) industries for the crucial role they play in the growth of the Tunisian manufacturing sector. The TCL sector has a high-ranking place in the Tunisian economy. It is the main part of the manufacturing sector and accounts for more than half of industrial employment and nearly half of all exports. The importance of the TCL industries in the Tunisian manufacturing sector is a reason for obtaining more knowledge on the patterns of productivity and efficiency growth for this key industry. An additional motivation for investigating patterns of productivity and efficiency for the TCL industry is that this industry will face substantial competitive pressure from foreign competitors along the gradual economic liberalization process beginning from 1995. This means that policy makers and industry agents need to obtain knowledge about this industry in order to be able to introduce several measures aimed at improving productivity sufficiently fast.

The Tunisian TCL industries are very labor-intensive industrial process. In general, these industries employ an unskilled working population and suffer from a lack of specialized labor. Small firms, with employees numbering in the range of 1-150, and family owned firms dominate the Tunisian textile industry.

The TCL industries are dominated by two types of firms. On the one hand some are totally oriented towards exportation, these have frequently foreign capital participation and are in partnership with investors principally from the European Union. On the other hand, some firms are oriented towards local market and are protected from competition. This protection does not encourage them to make upgrading efforts.

It is worth mentioning that the TCL industries, particularly the clothing industry, rely heavily on the importation of raw materials, principally woven fabrics, in order to meet production needs.

In the first stage, the data set has been “cleaned” of observations which could be seen as erroneous or which were clearly outliers. We have taken out firms that observed less than 5 periods; this is an unavoidable consequence of the dynamic nature of the model and panel data techniques used. In the estimation of a dynamic production function, we also required that all sample firms be observed consecutively. Thereby, the empirical analysis is based on an unbalanced panel consisting of a sample of 388 firms with between 5 and 12 annual and continuous observations over the period 1983-1994 (see table 1).[1] The data set includes: value added (y), capital stock (K) evaluated at historical values and labor (number of employees L). The number of employees is adjusted for whether it is part or fulltime equivalent employment. We have also some information about some time invariant characteristics such as activity and whether or not the firm is an exporting one, which allow us to make more meaningful statements about what types of firms were the most productive and the most efficient, and so forth.

Summary statistics of the data are presented in table 2. Activities dummy variables are used in the specification to reflect differences in production behavior with respect to activities. The main branches in the TCL industries are grouped into four major classes: Thread and carpets, hosiery, clothing and leather.

The third quartile of employment variable is of 144 employees reflecting the Tunisian industrial structure, which is dominated by the small firms.

3. 2. Empirical Results

3.2.1 Specification tests

Table 3 reports the estimation results of the dynamic production function defined in (6). The first column reports the results from the standard first differenced GMM estimator, the second column reports the results from the system GMM estimator and the third one reports the results from the static specification[2].

Both capital and labor are considered as predetermined and correlated with firm-specific effects error. Consequently, the instruments used for equations in first differences are observations on capital and labor dated (t-2) and earlier in addition to output dated (t-2) and earlier. For the system GMM estimator, we add the observations on $(\Delta k, \Delta l, \Delta y)$ dated (t-1) and time dummies as instruments for the equations in levels.

The validity of the instrument set is checked using a sargan test. This is asymptotically distributed as chi-squared under the null. The instruments used in the first differenced GMM or in the system GMM are not rejected by the Sargan test of over-identifying. Tests of no serial correlation in the v_{it} (M_1 and M_2) provide evidence to suggest that this assumption of serially uncorrelated errors is appropriate in the dynamic model as is shown in the first two columns[3]. We note that the dynamic production equation (see columns 1 & 2), performs well in conventional statistical terms with no second order serial correlation and with a sargan test for instrumental validity indicating that the instrument set and the residuals are not correlated. However, the test of no serial correlation of residuals is rejected in the static model. This indicates the presence of misspecification may be due to omission of the lagged variables. The hypothesis $a = b$, which implies a standard partial adjustment mechanism[4] is rejected. In fact, all coefficients associated with lagged inputs variables are statistically significant. The hypothesis $a = b = 1$, which implies that there is no difference between target and actual output, is also rejected. In fact, all coefficients associated with lagged dependent and inputs variables are statistically significant. In spite of this, we report results corresponding to the static specification solely for comparison with the dynamic specification. The difference between the results for the static model and the dynamic model are not negligible. On comparing columns (1) and (2) we can see an improvement in precision resulting from the exploitation of the extended moment conditions valid on levels equations, this is in conformity with the results of Blundell and Bond (1998b).

A Cobb-Douglas versus a translog specification was tested. The restricted Cobb-Douglas specification, which implies that all second-order input parameters are equal to zero, was rejected in favor of the translog specification.

The estimation of the system has made the identification of time-invariant variables effects possible. All of the industry-specific dummy variables were found to be significantly different from zero indicating a presence of unobserved industry effects. Also, the exporting dummy variable is found to be significantly different from zero indicating that the exporting firms are on average 6.5 percent more productive than domestically oriented firms.

The coefficient estimates for our preferred specification in column (2) shows that the coefficient on the lagged dependent variable is of 0.5 and is statistically significant. This confirms the fact that output takes time to reach its optimal level. The estimated coefficient on the lagged dependent variable is biased downwards if we use the differenced GMM estimates. The system GMM parameter estimates appear to be reasonable, the estimates of the factor elasticities are better determined than the differenced GMM estimate.

3.2.2 Input elasticities and returns to scale

Given that the coefficients of the translog production function can not be directly interpreted, we calculate the long-run elasticities of output with respect to each of

[1] Two years are lost in constructing lags and taking first differences, so that the estimation covers the period 1985-1994.

[2] We use DPD98 software implemented by Arellano & Bond (1998).

[3] These test statistics, distributed normally under the null of no serial correlation, are calculated and presented in the table 3.

[4] The partial adjustment model is nested in the error correction model.

the inputs as defined in equations (7) and (8). These elasticities vary over both time and firms. Heterogeneity due to differences in technologies has been adjusted for by assuming a translog form. In table 4 we report the long-run elasticities and returns to scale evaluated at the mean of the data and by key characteristics.

The elasticity of output with respect to labor is found to be around 0.94 and the elasticity of output with respect to capital stock is of 0.28. As can be seen from the standard deviation, the output elasticities with respect to labor and capital vary across observations. Output responds most to labor followed by capital. These values reflect the high labor-use in the Tunisian TCL industries. The relative importance of labor is very pronounced in the clothing activity (act3) and in the non-exporting firms relatively to the exporting ones. The exporting firms are more capital intensive than the non-exporting ones.

Returns to scale (RTS) are the sum of the input-elasticities. The elasticity of scale is around 1.23, and in most years close to this value, suggesting that the TCL industry has been using a technology with increasing returns to scale. Thereby, we do not find any evidence of significant change in the mean value of RTS over time. The data period is characterized by constancy in the scale of operations for the average firm in the sample. Almost all Tunisian textile firms seem to be below the optimal scale level. Furthermore RTS was also calculated for exporting firms and domestically oriented producers. The differences observed during the period 1983-1994 are not significant.

3. 2.3 Technical change, technical efficiency and productivity growth

Technical change is measured as the difference between the coefficients of two time dummies associated with two consecutive time periods. Results show, in general, a negative rate of technical change from 1986 to 1994. The rate of technical progress ranges from –6 percent in 1993 to 1.9 percent in 1987[5] (see figure 1). The mean value of technical change is -3.5 percent per annum. Tunisian firms experienced a technical regress over the period 1986-1993. The main reason for this technical regress is probably the lack of modernization of firms during this period. Innovation and experimentation are almost inexistent in the TCL industry during the studied period, while the primary activities are the ordinary production tasks.

Given the estimated parameters in Table 3, the technical efficiency is obtained from the equation (3). Descriptive statistics for technical efficiency measures derived from our preferred parameter estimates are given in Table 5. To conserve space, we report only the mean values of technical efficiency, which is a measure of structural efficiency. The sample mean technical efficiency is about 63 percent. This value indicates that firms, near the average, can improve their output level by 37 percent with the same set of inputs. Efficiency estimates are well within the bounds of those reported in other studies of Tunisian TCL industries such as Goaïed and Ben Ayed Mouelhi (2000). The sample mean efficiency is over-estimated if we choose a partial adjustment process, it is around 70 percent. It can be seen from table (5) and graph 2 that there is some decrease in efficiency of these firms over time, efficiency change ($\dot{EFF}$) is always negative. This result is in conformity with the rigidity of technologies and the lack of organizational progress in the TCL sector in Tunisia. The only positive efficiency growth rates are observed in 1987 and in 1991. The persistent deviations from the frontier may be an indication of rather low competitive pressures from foreign competitors in TCL for the 1983-94 period. Table 5 reports the efficiency measures by key characteristics of firms. We find that exporting firms are more efficient than non-exporting ones. Thus, the dualistic pattern between exporting firms and domestically oriented ones is confirmed by the empirical results.

Efficiency mean is of 66 percent for exporting firms and of 61 percent for non-exporting ones, and the efficiency decline is more pronounced for non-exporting firms (see figure 3). Participating in export markets brings firms into contact with international best practice and fosters learning, and efficiency growth. The smallest value of efficiency belongs to the clothing sector with on average an inefficiency of 40 percent.

The estimates of productivity growth obtained from equation (9) are given in table 5 and are also depicted in figure 4. The overall mean productivity growth range from –9.2 percent in 1993 to 3.5 percent in 1987,[6] with a mean of -4 percent. Positive rates were observed in 1987 and in 1990. Other than these years, productivity growth rates are negative. When we compare figures 1 and 3 we see the productivity growth rate follows the same pattern as the rate of technical change. This means that year-to-year shifts in the rate of technical change explain most of the fluctuations in productivity growth. The total factor productivity growth rate is always lower than the rate of technical change because of the negative contribution of efficiency change. Our evidence above indicates that during the sample years the firms experienced technical regress and a deterioration in technical efficiency. These firms also reported a negative rate of productivity growth, which we attribute particularly to the lack of innovative activities and investment in improved technologies. Other factors have made the

[5] Except the unexplained rate of 14% observed in 1990.

[6] Except the 12% observed in 1990 associated with the high technical change rate observed in that year.

conditions unfavorable for the firms belonging to Tunisian TCL industries, less capital intensive firms, intensive-use of unskilled labor and lack of human capital, family owned businesses, organizational resources and lack of competitive pressure from other producer countries, thus reducing their performance. Decision makers and industry agents must introduce measures aimed at limiting these constraints and improving technical conditions for the TCL firms before the implementation of the tariff abolishing plan. An action plan must be implemented notably including a restructuring and industrial upgrading program of TCL industries, training, old technology, marketing and the international promotion of the sector. Public authority must encourage for the development of a modern, export-oriented industry.

4. Conclusion

In this paper we estimate technical efficiency from dynamic and stochastic frontier production function, which have been adjusted to account for output adjustment delay. This adjustment is modeled via an error correction model type. We specifically accommodate the possibility that firms may not be at their optimal output level at any given point in time. In so doing, we are able to identify the determinants of optimal output rather than observed output.

The estimation of dynamic error components models is considered using an alternative to the standard first differenced GMM estimator. It is a system GMM estimator deduced from a system of equations in first differences and in levels and exploiting extra moment restrictions. The system GMM estimator offers efficiency gains relative to the first differenced GMM estimator. It is interesting in estimating technical efficiency because it permits the identification of the time-invariant variables effects in contrast to the first differenced GMM estimator. This makes it possible to control for possible differences in optimal output among firms of different characteristics.

The empirical analysis is based on an unbalanced panel consisting of 388 firms from the Tunisian textile, clothing and leather industries observed during 1983-1994. A translog form for the production function is used. Statistical tests are used to choose the appropriate instruments in implementing GMM estimations.

In comparing the results obtained when using the two estimators that is, GMM from first differences equations and GMM from system, we observe that the two sets of results differ substantially. In fact, the system GMM estimations are more precise than the usual first-differenced estimations. The gain in precision comes from exploiting the additional moment restrictions, which are not rejected by tests. The coefficients of time-invariant variables appear to be statistically significant. We obtain much more reasonable results using the system GMM estimator.

Estimation results suggest that the error correction mechanism is superior to partial adjustment mechanism in modeling output adjustment.

Our results suggest that TCL industry has been using a technology with increasing returns to scale. Thereby, we do not find any evidence of significant increase or change in the mean value of RTS over time. This indicates that the data period is characterized by constancy in the scale of operations for the average firm in the sample. Almost all Tunisian textile firms seem to be below the optimal scale level. We observe a technical regress during the period, in conformity with the rigidity of technology and the lack of organizational progress and modernization in the TCL sector in Tunisia. Innovation and experimentation are almost inexistent in the TCL industry, while the primary activities are the ordinary production tasks.

The mean efficiency level resulting from the system GMM estimates is about 63 percent indicating that firms, near the average, can improve their output level by 37 percent with the same set of inputs. The temporal pattern of technical efficiency shows decline in mean efficiency over time. The persistent deviations from the frontier may be an indication of rather low competitive pressures from foreign competitors in TCL for the 1983-94 period. The sample mean efficiency is over-estimated if we choose a partial adjustment process, it is around 70 percent.

We find that exporting firms are more efficient than the non-exporting ones and that the decline in efficiency is more pronounced for the non-exporting firms. Participating in export markets brings firms into contact with international best practice and fosters learning, productivity growth and efficiency growth. The smallest value of efficiency belongs to the clothing sector with on average an inefficiency of 40 percent.

Productivity differentials between activities are found to be significant. Productivity growth rates are negative with a mean of -4 percent. The contribution of the technical change to productivity growth is negative for most of the years. The total factor productivity growth rate is lower than the rate of technical change because of the negative contribution of efficiency change.

Our evidence above indicates that during the sample years the firms experienced technical regress and deterioration in technical efficiency. These firms also reported a negative rate of productivity growth, which we attribute particularly to the lack of innovative activities and investment in improved technologies. Decision makers and industry agents must introduce measures aimed at limiting these constraints and improving technical conditions for the TCL firms before total liberalization.

References

Ahn S.C. and P. Schmidt.1995. "Efficient Estimation of Models for Dynamic Panel Data", *Journal of Econometrics*, Vol. 68: 5-28.

Ahn S.C. and P. Schmidt. 1997. "Efficient Estimation of Dynamic Panel Data Models: Alternative Assumptions and Simplified Estimation." *Journal of Econometrics*, Vol. 76: 309-321.

Arellano M. and S. Bond. 1991. "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *Review of Economic Studies*, Vol. 58: 277-297.

Arellano M. and O. Bover. 1995. "Another Look at the Instrumental-Variable Estimation of Error-Components Models." *Journal of Econometrics*, Vol. 68: 29-51.

Baltagi B.H. 1995. *Econometric Analysis of Panel Data*. John Wiley and Sons.

Baltagi B.H and J. M.Griffin. 1988. **"**A General Index of Technical Change." *Journal of political Economy*, Vol. 96: 20-41.

Blundell R. and S. Bond. 1998a. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." *Journal of Econometrics*, Vol. 87: 115-143.

Blundell R. and S. Bond. 1998b. **"**GMM Estimation with Persistent Panel Data: An Application to Production Functions." Paper presented at the Eighth International Conference on Panel Data. Goteborg University.

Goaïed M. and R. Ben Ayed-Mouelhi. 2000. "Efficiency Measurement with Unbalanced Panel Data: Evidence on Tunisian Textile, Clothing and Leather Industries." *Journal of Productivity Analysis*, Vol.13:249-262.

Nickell S.1996. "Competition and Corporate Performance." *Journal of political Economy*, Vol. 104: 724-746.

Nickell S., S.B. Wadhwani, B. Sushil and M. Wall. 1992. "Productivity Growth in U.K Companies, 1975-1986." *European Economic Review*, Vol. 36: 1055-85.

Kumbhakar S.C, A. Heshmati and L. Hjalmarsson. 2000. "How Fast do Banks Adjust? A Dynamic Model of Labor-use with an Application to Swedish banks." *Working paper series in Economics and Finance*, n° 411.

Figure 1: Technical Change Over Time

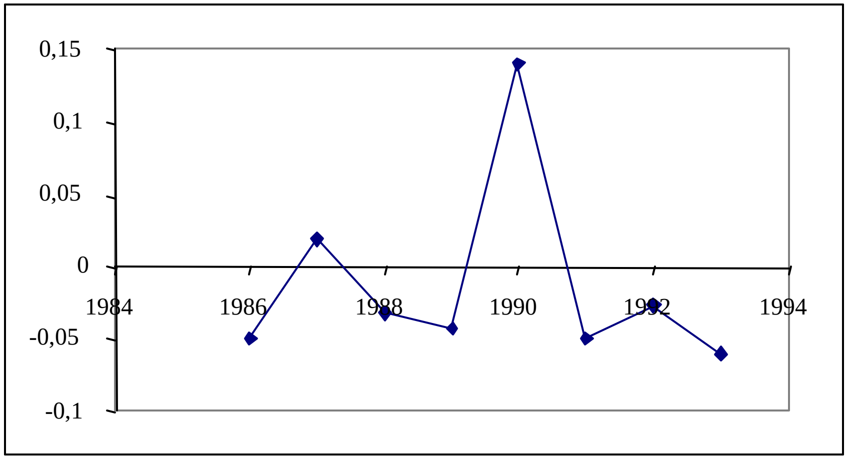

Figure 2: Efficiency Mean Over Time

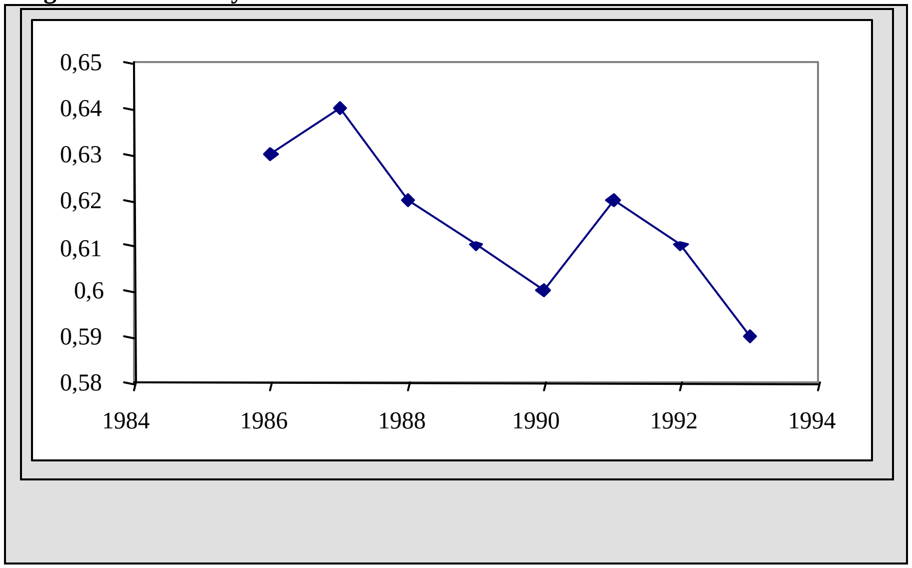

Figure 3: Efficiency Over Time for Exporting and Non-exporting Firms

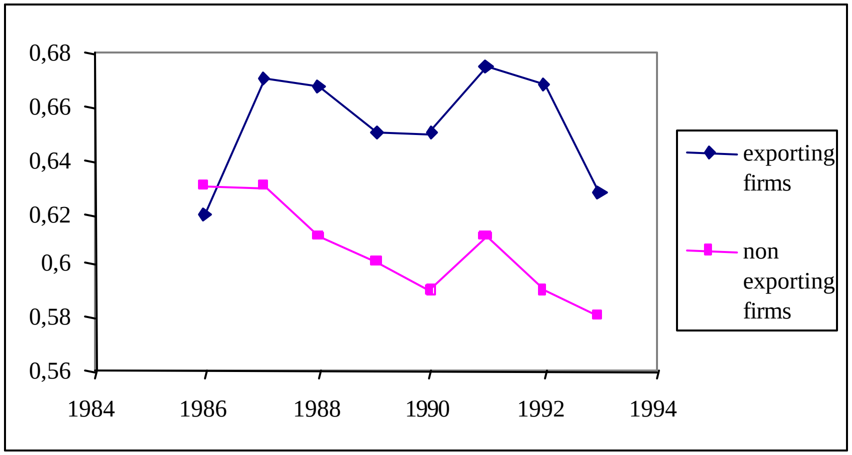

Figure 4: Productivity Growth Over Time

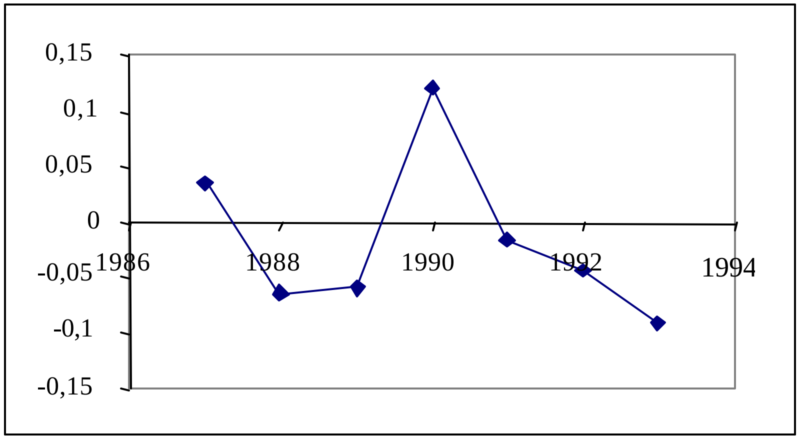

Table 1: Number of Firms by Periods

Periods	5	6	7	8	9	10	11	12
Firms	89	41	37	40	41	40	68	32

Table 2: Summary Statistics of the Variables

Variables	**Definition and measurement**	**Mean**	**Standard deviation**
L	Number of employees	110	154.4
K	Capital stock in 1990 prices (Dinars)	1486949	4509211
Y	Value added in 1990 prices (Dinars)	560927	1415072
Act1	Thread, materials and carpets	0.248	
Act2	Hosiery	0.093	
Act3	Clothing, reference class	0.476	
Act4	Leather, fine leather articles and shoes	0.18	
dpex	Domestically oriented producers	0.74	

Table 3: Parameter Estimates

Coefficients	Dynamic specification GMM-DIF	GMM-SYS	Static specification GMM SYS
Y(-1)	0.29	0.52	………..
	(0.02)	(0.02)	
Ln K	-2.62	-1.16	-1.02
	(0.41)	(0.23)	(0.126)
(ln K)(-1)	1.59	0.73	………..
	(0.37)	(0.23)	
ln L	1.53	1.28	2.82
	(0.34)	(0.23)	(0.11)
(ln L)(-1)	0.53	0.18	…………
	(0.41)	(0.19)	
$(\ln K)^2$	0.14	0.083	0.091
	(0.018)	(0.012)	(0.005)
$(\ln K^2)(-1)$	-0.062	-0.044	……………
	(0.018)	(0.01)	
$(\ln L)^2$	0.16	0.2	0.2
	(0.025)	(0.013)	(0.008)
$(\ln L^2)(-1)$	-0.049	-0.125	……………
	(0.025)	(0.014)	
(lnKxlnL)	-0.19	-0.174	-0.28
	(0.033)	(0.021)	(0.011)
(ln KlnL)(-1)	-0.025	0.049	……………
	(0.038)	(0.017)	
dpex	………	-0.076	-0.3
		(0.028)	(0.027)
act1	……….	-0.17	-0.33
		(0.026)	(0.032)
act2	………..	-0.17	-0.27
		(0.027)	(0.024)
act3	…………	-0.09	-0.14
		(0.022)	(0.026)
M_1: 1st order serial correlation	-6.823	-8.193	-4.637
M_2 : 2nd order serial correlation	-0.886	-0.128	-3.863
Sargan: Instrumental validity	170.29	234.6	294.47
Df	154	205	255

Notes: a) Coefficients on time dummies are included in all specifications but not reported here. b)-M_1 and M_2 are tests for first - order and second-order serial correlation in the first -differenced residuals (see Arellano & Bond (1991) for details). c) Standard errors are reported in parentheses. d) The instruments used in each equation are: $y_{it-2},...,y_{i1},k_{it-2},...,k_{i1},l_{it-2},...,l_{i1}$ for equations in first differences and $\Delta y_{it-1},\Delta k_{it-1},\Delta l_{it-1}, dpex$, industries dummies and year dummies for levels equations.

Table 4: Mean estimates of input elasticities (Ey/L and Ey/K) and return to scale (RTS) by activity and for exporting and non-exporting firms.

	Ey/L	Ey/K	RTS
Act 1	0.75	0.4	1.16
Act 2	0.94	0.29	1.23
Act 3	1.11	0.17	1.28
Act 4	0.89	0.33	1.22
Exporting	0.86	0.37	1.23
Non - Exporting	0.98	0.24	1.23
Overall means	0.94	0.28	1.23
Std dev	(0.25)	(0.18)	(0.084)

Table 5: Efficiency, Efficiency Change, Technical Change and Productivity Growth

	EFF	$\dot{EFF}$	TC	Productivity Growth
Means by year				
1986	0.63	…….	-0.05	…….
1987	0.64	0.016	0.019	0.035
1988	0.62	-0.031	-0.034	-0.065
1989	0.61	-0.016	-0.044	-0.06
1990	0.60	- 0.016	0.14	0.12
1991	0.62	0.033	-0.05	-0.017
1992	0.61	-0.016	-0.027	-0.043
1993	0.59	- 0.032	- 0.06	- 0.092
Means by activity				
Act 1	0.65			
Act 2	0.63			
Act 3	0.60			
Act 4	0.68			
Means for exporting and non exporting firms				
Exporting	0.66			
Non-exporting	0.61			
Overall mean	0.63		-0.035	-0.04