COMPARATIVE MEASURES OF TECHNICAL EFFICIENCY FOR FIVE HUNDRED FRENCH WORKERS' COOPERATIVES

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1. INTRODUCTION

While the amount of theoretical literature comparing the self-managed firm to its capitalist twin is now quite large, comparative empirical research is still underdeveloped, especially that concerning the assessment of the respective economic performance of these firms. A few authors have tried to make progress in this direction but a fairly complete list of such contributions would be quite small.[1] Moreover, it has always been difficult to fulfill the conditions required for a very thorough analysis and reliable results:

1. coverage of a sufficient number of self-managed firms to avoid limits of case studies,
2. availability of similar data for a significant group of traditional firms operating in the same precisely defined industries, and
3. use of a coherent set of criteria covering most of the important aspects of the firms' economic performance.

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In an attempt to meet these requirements better, we have developed elsewhere a detailed comparative financial analysis with some 25 ratios for a sample of about 500 French workers' cooperatives (Sociétés Coopératives Ouvrières de Production—SCOP) over ten years (Defourny 1986a, 1987). The results for coops in each of the 14 industries were compared to averages computed at the sectoral level on the basis of very similar although aggregate data.

In this paper, we would like to supplement that financial analysis with an econometric approach of the comparative technical efficiency of French workers' coops. More precisely, on the basis of the same data and starting from the estimation of production functions, we shall try to build the production frontier, specific to each activity. This rather peculiar technique, virtually unused in the study of coops and other self-managed firms, will allow us to calculate, in percentages, an efficiency degree of the firms belonging to each sector. This parameter will enable us not only to compare SCOPs to their capitalist counterparts but, to a certain extent, groups of SCOPs between each other as well.

Our analysis is formed of two main parts. Section 2 is a methodological survey in which we review different ways of designing and estimating production frontiers empirically. We first briefly introduce parametric frontiers estimated by statistical methods (Section 2.A), then we present two classes of such frontiers, stochastic (Section 2.B) and deterministic (Section 2.C). For each of these groups, we try to point out advantages and limits of different procedures as to (1) model specification, (2) model estimation, and (3) technical efficiency measurement. For illustrative purposes, we also apply these various procedures to our sample of cooperative individual observations and we estimate production frontiers for 14 activities in which large numbers of SCOPs can be found.

Section 3 is devoted to the comparative efficiency analysis itself. On the basis of the previous section, we first choose the kind of frontier that is most appropriate given the data we have for SCOPs and capitalist firms (Section 3.A). Then average degrees of efficiency are computed for both groups of firms in each sector without any size distinction (Section 3.B). Finally, comparisons by size categories are developed (Section 3.C) and most interesting results linking SCOPs' comparative efficiency to firm size and activity are presented in Section 3.C.2. Concluding remarks summarize the main steps and results of the study; they stress the limitation data often impose upon empirical frontier analysis.

2. BUILDING FRONTIERS AND MEASURING THE TECHNICAL EFFICIENCY OF SCOPS

Some authors have recently given excellent surveys of the literature dealing with the estimation of production frontiers.[2] We shall therefore only use a few necessary definitions and distinctions in order to establish clearly the sort of approach we favor. We shall then give more details about the specific methods we use.

A. A Few Reference Points

To start with, we shall note that there still exists a certain confusion in the use of terms such as frontiers and production functions. On a theoretical level, indeed, a production function is a frontier since it expresses the maximum quantities of output that can be obtained with fixed quantities of output that can be obtained with fixed quantities of inputs, given the existing technology. On the other hand, at the empirical level, the production functions estimated in most econometric studies are average functions that cross the cloud of points representing given situations and that do not form, at all, the envelop of those points. It is only since the studies carried out by Farrell (1957) and particularly over the last decade that researchers have been trying to estimate, empricially, "frontier" production functions. We shall not, however, overestimate the difference between average and frontier functions for, in most cases, including ours, models have the same definition for both, except for a term of technical inefficiency in the constant term.

As far as the production frontier concept itself is concerned, we shall stress that it may be absolute or relative. In the former hypothesis, the frontier is defined theoretically on the basis of the knowledge of technical operations that are necessary to turn inputs into outputs. On the other hand, if the frontier is built on the basis of a set of given situations, it corresponds to what Farrell describes as the "best practice" and is only relative. In this case, indeed, there is no guarantee that the estimated frontier really represents the maximum outputs obtainable. It is, nevertheless, this last approach that is used in most empirical studies.[3]

There are many ways of classifying the estimation procedures. First of all, a distinction must be made between parametric and nonparametric methods where there is no specified analytical form to estimate the production frontier.[4] On the other hand, for the parametric methods, a model explicitly defines the frontier whose parameters must be estimated. In order to do so, one may use either linear or quadratic programming, but these remain descriptive methods since nothing is known about the properties and the qualities of the estimators obtained in this way. That is why we prefer to use inferential or statistical methods such as ordinary least squares (OLS) or maximum likelihood (ML). Thanks to the assumptions they imply about the regressors and the disturbance term, these methods give estimators whose properties make statistical inference possible.

In this work, we shall confine ourselves to the parametric frontiers and to their estimation by inferential procedures.[5] Besides, these methods will only be considered within the context of direct estimation of frontiers, which means that we shall exclude cases where frontiers are built from the estimation of cost functions, owing to the duality of any production function.

Within this perimeter, although strictly limited, we shall see that many approaches to technical efficiency are still possible. More precisely, in our attempts to define the SCOPs' efficiency, we shall work with frontier production functions that may be either stochastic or deterministic. In the case of deterministic production functions, we shall put forward three different ways of estimating the average efficiency of a given group of firms.

B. Stochastic Frontiers and Average Technical Efficiency

All parametric methods have one thing in common: they specify the relation between observed productions and the frontier function by associating to the latter a term expressing the distance that separates the productions from the frontier. Thus, if the vector X expresses the quantities of n inputs used to produce a single output noted by the variable Y, and if the technically efficient transformations of inputs into output are represented by the parametric function

$$Y = f(X) \qquad \text{or} \qquad \ln Y = \ln[f(X)]$$

then the relation between this frontier and the observed productions Y^o can be expressed as

$$Y^o = f(X)e^{-d} \qquad \text{or} \qquad \ln Y^o = \ln[f(X)] - d$$

The difference between stochastic frontiers and deterministic frontiers lies in the use they make of the distance d. We have a deterministic frontier if we assume that technical inefficiency alone explains the difference between an observed production Y^o and the maximum quantity Y^x that could have been produced with the same quantities of inputs. In the case of a stochastic frontier, the difference is believed to come from technical inefficiency, but from some other phenomena as well, such as measurement errors, omission of explicative variables, or random shocks beyond the control of the firm's managers. This is why the distance d is then split up into two independent elements:[6]

$$d = u - v \qquad \text{or} \qquad e^{-d} = e^{-u+v}$$

Here v expresses a symmetric random term that includes the effects of factors external to the firm and the measurement errors, whereas u represents technical inefficiency in itself and is, by definition, one-sided ($u \geqslant 0$, and thus $0 \leqslant e^{-u} \leqslant 1$).

This last approach seems to be realistic and more appropriate, since we will be working with individual observations on SCOPs. With sector averages, we could possibly leave aside the random term v especially by assuming that

measurement errors offset each other in the averages. But with individual observations, it is impossible to ignore what corresponds to the classical disturbance term of econometric models.

1. Specification of the Model

We shall see later that stochastic frontiers also have important disadvantages. For now, though, we shall only try to estimate, in a stochastic form, the production frontier of 14 groups of SCOPs corresponding to the different industries in which they operate. In its most general expression, our statistical model is expressed by

$$Y^o = f(X)e^{u-v}$$

As far as the frontier $f(X)$ is concerned, we consider three different specifications for each sector: a Cobb–Douglas function under log-linear form, the linear approximation of CES suggested by Kmenta (1967), and finally, the translog form. All three are identically analyzed. In the following, we simply take the example of the Cobb–Douglas function with the variable V for the firm's value added, L for the number of workers, K for the fixed assets, and a dummy variable d_k for each of the nine years covered from 1971 through 1979 ($k = 1, 2, \ldots, 9$):[7]

$$\ln V_{it} = \alpha_0 + \sum_k \alpha_{1k} d_{kit} + \alpha_2 \ln K_{it} + \alpha_3 \ln L_{it} + v_{it} - u_{it} \qquad (1)$$

(where i is the index of the ith SCOP and $t = 1, 2, \ldots, 9$).

We assume that variables K, L, and d are exogenous and that the error term v is independently and identically distributed according to a normal law of zero mean and of variance σ_v^2. Finally, we must specify the distribution of the one-sided residual u (or of e^{-u}). Afriat (1972) was the first to put forward a two-parameter beta distribution for e^{-u} and Richmond (1974) showed that this implied a gamma distribution for u. Schmidt (1976) considered an exponential and a seminormal distribution for u.[8] Finally, Aigner, Lovell, and Schmidt (1977) have suggested a truncated normal distribution for the term u.

It is rather difficult to choose the kind of distribution we want for u since this conditions the results of the model's estimates. With the maximum likelihood method, both $\hat{\alpha}_i$ estimators and the efficiency measures vary according to the distribution we choose, whereas with the corrected least squares method, only the efficiency measures vary. In fact, nothing implies that we should use a specific distribution; therefore, we shall consider, for each sector frontier, both an exponential and a gamma distribution for the term u.[9]

2. Model Estimation

We cannot estimate our model, as specified in Eq. (1), with the OLS method. In fact, the OLS estimator of the constant α_0 would be biased since the term u has a positive mean when the technical efficiency is not maximum for all observations. To circumvent this difficulty, Richmond (1974) made the following proposal:[10] if μ_u is the mean of the term u, Eq. (1) should be rewritten as follows:

$$\ln V_{it} = (\alpha_0 - \mu_u) + \sum_k \alpha_{1k} d_{kit} + \alpha_2 \ln K_{it} + \alpha_3 \ln L_{it} + \varepsilon_{it} \qquad (2)$$

with $\varepsilon_{it} = \mu_u - u_{it} + v_{it}$.

The new error term ε, being of 0 mean, satisfies all the usually required conditions except normality, and Eq. (2) can be estimated with the OLS method. To go from the "average" production function thus obtained to the production frontier, we only need to correct the constant $(\alpha_0 - \mu_u)$, estimated by the OLS method, by adding the mean μ_u of the term u to it. This is why this is called the corrected ordinary least squares (COLS) method.[11]

The correction of the OLS constant term requires that we obtain a consistent and unbiased estimator of μ_u. Therefore, if we have assumed a specific distribution for u, such an operation is possible when we start from the central moments of the OLS residuals. Indeed, the third central moment of the ε error is equal to the third central moment,[12] its sign changed, of the term u and $\mu_3(u)$ itself is linked to the mean μ_u that we want to estimate.[13]

In other words, the OLS estimator of the third central moment of ε [written $\hat{\mu}_3(\varepsilon)$] gives a consistent estimator of μ_u:[14]

$$\hat{\mu}_u = \begin{cases} [\hat{\mu}_3(\varepsilon)/2]^{1/3} & \text{for an exponential distribution of } u \\ -\hat{\mu}_3(\varepsilon)/2 & \text{for a gamma distribution of } u \end{cases}$$

The correction of the OLS constant term, that is to say, the shifting of the average production function in order to obtain the production frontier, will therefore be different according to the distribution we choose for u.

The part of the ε total variance attributable to the random term v will also vary according to the distribution of u:

$$\frac{\hat{\sigma}_v^2}{\hat{\mu}_2(\varepsilon)} = \begin{cases} 1 - \dfrac{[\hat{\mu}_3(\varepsilon)/2]^{2/3}}{\hat{\mu}_2(\varepsilon)} & \text{for an exponential distribution of } u \\ 1 + \dfrac{\hat{\mu}_3(\varepsilon)}{2\hat{\mu}_2(\varepsilon)} & \text{for a gamma distribution of } u \end{cases}$$

Finally, and this is one of the main disadvantages of the stochastic frontiers, the latter may not exist: for the distributions of u we are interested in, if $\hat{\mu}_3(\varepsilon)$ is positive then $\hat{\mu}_u$ is negative. And a downward shifting of the average

production function is not meaningful at all as far as the building of a frontier is concerned.

3. Technical Efficiency Measurement

The technical efficiency measurement itself shows another limitation of the stochastic frontiers: this measurement can only be carried out at the level of all observations but not individually. It is, indeed, impossible to identify, for each residual $\hat{\varepsilon}_{it}$, the part attributable to factors external to the firm's management (represented by the normal random term v) and the part attributable to inefficiency (represented by u). Besides, a few observations can be found above the estimated frontier.[15] On the other hand, the assumptions made about the distribution of v, especially that v has a 0 mean, allow us to estimate the mean of the inefficiency term u.

As far as our analysis is concerned, this means that we will only be able to get a measure of the average technical efficiency of each group of SCOPs corresponding to a specific sector. To define this measure, we have to start once again from Richmond's study (1974) on deterministic frontiers. By comparison with our model's general expression for a stochastic frontier, that is, $Y^\circ = f(X)e^{v-u}$, the deterministic-frontier model can be written $Y^\circ = f(X)e^{-u}$. For Richmond, a straightforward measure of the technical efficiency average degree for all the firms that are covered is thus given by[16]

$$E(e^{-u}) = E(z) \qquad \text{with} \qquad z = e^{-u}$$

For a gamma distribution of u, the same author builds the distribution of z and shows that

$$E(z) = 2^{-\mu_u}$$

Meeusen and van den Broeck (1977) take up the same average efficiency measure $E(e^{-u})$ for the case of a stochastic frontier.[17] Moreover, they use the same method as Richmond, by assuming an exponential distribution for u, and obtain the following expression of technical efficiency:

$$E(z) = 1/(1 + \mu_u)$$

Since we already have a consistent estimator of μ_u based on the third moment of the OLS residuals, all we have to do is to use it again:

$$E(z) = \begin{cases} \dfrac{1}{1 - [\hat{\mu}_3(\varepsilon)/2]^{1/3}} & \text{for an exponential distribution of } u \\ 2^{\hat{\mu}_3(\varepsilon)/2} & \text{for a gamma distribution of } u \end{cases}$$

and it is easily verified that $E(z)$ is only meaningful $(0 \leqslant z \leqslant 1)$ if $\hat{\mu}_3(\varepsilon)$ is nonpositive.

Finally, as Schmidt and Lin (1984) sugget, once we have calculated $E(z)$, we can still see whether technical efficiencies are significant by submitting the residuals $\hat{\varepsilon}_{it}$ to the nonnormality test based on the asymmetry coefficient $b_1^{1/2}$.[18] These authors consider that the greater the technical inefficiencies, the more asymmetrical the distribution of the $\hat{\varepsilon}_{it}$ must be, since the latter represents the sum of a normal variable (v) of 0 mean and of a nonpositive variable ($-u$) representing the inefficiency. The existence of significant technical efficiencies will thus be confirmed if the test makes it possible to reject the zero hypothesis of normality for residuals $\hat{\varepsilon}_{it}$.[19]

4. *The Results*

As we have seen, the first step in our empirical approach consists in estimating an average production function for each sector. This is what we do, starting from Eq. (2) and from similar equations for the two alternative specifications (Kmenta's CES and translog). Table 1 gives the results of these estimates for the production function specification that, on the F-tests basis, is the most appropriate for each sector. We can observe that the Cobb–Douglas and translog forms are used respectively seven and six times, whereas the CES linear approximation is only used once, for the carpentry sector.

We then have to correct the constant term of each average production function by adding the mean $\hat{\mu}_u$ to it. This mean is estimated differently depending on the exponential or gamma distribution of the term u. We therefore obtain, for each sector, two stochastic frontiers with respect to which the average efficiency $E(z)$ can be calculated on the basis of the formulas just mentioned. These results are shown in the first and second columns of Table 2.

Analysis of this table indicates that an estimate of the average efficiency $E(z)$ has not been possible for four sectors: whatever specification the production function has for public works, plumbing, furniture, and the telephone industry, the third moment of the OLS residuals is positive and prevents the building of the frontier.

When the average technical efficiency can be calculated, it is always much greater if we assume a gamma rather than an exponential distribution for u. Depending on the different sectors, it varies from 94 to 99.9% in the first case and from 73.1 to 91% in the second one. For each industry, indeed, both frontiers are identical but for the constant term since they are built from the same average production function. And this constant is greater with an exponential distribution of u because the estimator $\hat{\mu}_u$ is thus greater than it is with a gamma distribution.[20]

Table 1. Average Production Functions for 14 Industries[a]

	Carpentry	*Bricklaying*	*Painting*	*Public Works*	*Plumbing*	*Electricity*	*Printing*	*Related to Printing*	*Metal Construction*	*Sheet Metal*	*Furniture*	*Telephone*	*Architecture*	*Consulting*
Constant term	3.070***	2.957***	3.134***	3.615***	3.529***	0.788*	1.341***	1.822*	1.721***	3.004***	1.403***	3.124***	3.195***	3.153***
		(46.5)	(35.8)	(14.5)	(37.2)	(1.71)	(4.79)	(1.80)	(3.51)	(16.3)	(3.07)	(23.2)	(17.9)	(8.58)
Yearly dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ln *K*	0.052**	0.053***	0.130***	0.038	0.156***	−0.790***	0.428***	0.013	0.490***	0.065*	1.081***	0.340***	0.077*	0.136**
	(2.41)	(3.19)	(6.56)	(0.27)	(5.97)	(−5.36)	(4.02)	(0.01)	(2.89)	(1.91)	(3.61)	(9.22)	(1.87)	(2.24)
ln *L*	0.948***	1.008***	0.862***	0.724***	0.750***	3.501***	1.280***	2.149*	1.082***	0.977***	0.371	0.612***	1.019***	1.149***
	(34.0)	(41.8)	(29.7)	(5.07)	(22.3)	(13.9)	(7.26)	(1.91)	(3.02)	(14.5)	(1.07)	(12.5)	(17.2)	(10.0)
$(\ln K/L)^2$	0.024***													
	(3.38)													
$(\ln K)^2$				0.074***		−0.026***	0.011	−0.006	0.020		0.005			
				(2.91)		(−3.70)	(0.60)	(−0.03)	(0.78)		(0.01)			
$(\ln L)^2$				0.160***		−0.574***	0.051	−0.373	0.149		0.472***			
				(4.65)		(−7.96)	(0.82)	(−1.46)	(1.43)		(3.09)			
$\ln K \ln L$				−0.189***		0.317***	−0.115*	0.141	−0.184**		−0.401**			
				(−3.57)		(5.23)	(−1.88)	(0.32)	(−2.04)		(−2.15)			
R^2 adj.	0.960	0.967	0.904	0.957	0.940	0.942	0.959	0.917	0.913	0.926	0.934	0.993	0.923	0.830
Number of obs.	316	310	294	167	155	81	252	54	85	80	67	31	72	86

[a]The figures in parentheses represent the values of the variable t for Student's test.
*Significant at 0.10 level. **Significant at 0.05 level. ***Significant at 0.01 level.

Table 2. Various Measures of the Scop Average Technical Efficiency in 14 Industries

	Stochastic frontiers[a]			Deterministic frontiers			
	E(z) (%)			E(z) (%)		Weighted average (%) of individual efficiency	Efficiency (%) of the sectoral average SCOP (over 9 years)
	Exponential distribution		Gamma distribution	Exponential distribution	Gamma distribution	MOLS	Exponential distribution
Carpentry	90.7 (0.82)	NR**	99.9 (0.98)	80.5	96.0	46.4	77.1
Bricklaying	89.8 (0.77)	NR*	99.9 (0.97)	80.8	96.1	40.1	80.6
Painting	91.0 (0.86)	NA	99.9 (0.99)	79.0	95.2	44.7	73.5
Public works		$\mu_3 > 0$		82.6	97.0	35.6	84.8
Plumbing		$\mu_3 > 0$		81.5	96.5	29.2	76.0
Electricity	73.1 (0.15)	NR**	94.0 (0.48)	70.6	88.7	35.0	69.6
Printing	75.4 (0.10)	NR**	95.0 (0.37)	74.3	92.1	44.6	70.0
Related to printing	78.2 (0.25)	NR**	98.5 (0.79)	75.6	93.0	52.6	64.9
Metal construction	85.3 (0.67)	NR*	99.6 (0.94)	77.0	94.0	39.6	73.7
Sheet metal	86.2 (0.79)	NA	99.7 (0.97)	74.2	92.0	44.8	76.6
Furniture		$\mu_3 > 0$		75.8	93.1	38.1	81.0
Telephone		$\mu_3 > 0$		87.6	98.6	82.4	75.9
Architecture	87.4 (0.65)	NA	99.8 (0.95)	80.4	96.0	59.2	80.3
Consulting	78.2 (0.70)	NA	98.5 (0.92)	66.3	83.6	26.9	65.0

[a]The figures in parentheses represent the part of the residuals variance attributable to the normal random term. NR*, normality rejected at the 0.05 significance level; NR**, normality rejected at the 0.01 significance level; NA, normality accepted at the 0.05 significance level.

The SCOPs that are found to have the highest average levels of efficiency are the ones belonging to the painting, carpentry, and bricklaying industries. The SCOPs with the lowest levels of efficiency are those in electricity, printing, and industries related to printing and consulting sectors. Yet, it is rather risky to compare the different sectors since the concept of technical efficiency is relative to each sector: the frontiers are defined on the basis of observed productions and do not necessarily represent the theoretically possible maximum outputs. Besides, this is confirmed by the results of the nonnormality test made on the residuals $\hat{\varepsilon}_{it}$ of each average function (the results are given in Table 2 as NA or NR). Since the reference standard changes from one sector to the next, average efficiencies that may be practically identical for two groups of SCOPs can lead to diametrically opposite conclusions concerning the existence of significant technical inefficiencies. This statement can easily be proved by comparing, for example, the carpentry and the painting industries or the consulting sector and the industries related to printing.

In the first two columns of Table 2, in parentheses, are the part of the $\hat{\varepsilon}_{it}$ residuals total variance attributable, in each case, to the normal random term. This additional indication shows fairly well the relevance of stochastic frontiers, that is, the relevance of an approach that does not interpret any difference vis-à-vis the frontier in terms of productivity: the percentage of the variance attributable to the random term v is, in most cases, greater than 70%. This percentage, quite logically, is the smallest for sectors in which SCOPs' technical efficiency is the weakest.

Yet, such subtle analysis, based on stochastic frontiers, is not good as far as comparisons are concerned. We have seen, indeed, that if we estimate such a frontier for all firms, it is impossible to calculate individual technical efficiencies or even the average efficiency of some subgroups.[21] Moreover, since we have just proved the necessity for the groups of firms we want to compare, to have common frontiers, we give up working with stochastic frontiers and start exploring all the possibilities offered by the deterministic frontiers. We shall observe, however, to what extent the SCOPs' average efficiency changes when using one type of frontier or the other.

C. Deterministic Frontiers and Average Technical Efficiency

Our aim is to define technical efficiency on the basis of deterministic production frontiers, by following exactly the same stages we did in the case of stochastic frontiers. We can, however, forget the developments concerning the random-error term integrated to the latter.

1. Model Specification

Since we now assume that differences vis-à-vis the frontier only arise from technical inefficiencies, our model for a Cobb–Douglas function can be written

$$\ln V_{it} = \alpha_0 + \sum_k \alpha_{1k} d_{kit} + \alpha_2 \ln K_{it} + \alpha_3 \ln L_{it} - u_{it} \tag{3}$$

Leaving out the normal random term undeniably implies a great loss of realism since we now know neither the measurement error effects nor the influence of external factors on the firms. But the true importance lies in evaluating the significance of this simplification of the assumptions in a comparative perspective. We shall try to make such an evaluation later.

2. Model Estimation

In Eq. (3), the term u has a positive mean as long as all the observations do not lie on the frontier. We shall therefore use the COLS method to estimate our model. In other words, we shall modify Eq. (3) in order to obtain a zero mean for the residuals:

$$\ln V_{it} = (\alpha_0 - \mu_u) + \sum_k \alpha_{1k} d_{kit} + \alpha_2 \ln K_{it} + \alpha_3 \ln L_{it} - \varepsilon_{it} \tag{4}$$

with $\varepsilon_{it} = \mu_u - u_{it}$.

When we use the OLS method, the coefficients of this equation have, indeed, the same values as the coefficients of the average production function (2). Thus, once again, Table 1 provides us with the basis on which we shall build the production frontiers. On the other hand, μ_u will be estimated differently because this time, the variance of the $\hat{\varepsilon}_{it}$ residuals gives us a consistent and unbiased estimator of the u variance.[22] In accordance with the links existing between the first two central moments of u, and if we choose for this term a specific distribution, we can write (see note 1):

$$\hat{\mu}_u = \begin{cases} [\hat{\mu}_2(\varepsilon)]^{1/2} & \text{for an exponential distribution of } u \\ \hat{\mu}_2(\varepsilon) & \text{for a gamma distribution of } u \end{cases}$$

And, when we add $\hat{\mu}_u$ to the constant obtained with the OLS method, we have two deterministic frontiers for each industry.

Since $\hat{u}_{it}\ (= \hat{\varepsilon}_{it} - \hat{\mu}_u)$ exclusively represents technical inefficiency, we should be able to calculate an efficiency degree for each observation. However, with the COLS method there is no guarantee that the shift of the average production function is such that all observations can be found beneath or on the frontier. To solve this problem, Greene (1980) suggests using another method to correct the constant of the average function: modified ordinary least squares (MOLS) method. It consists in replacing $\hat{\mu}_u$ by the highest positive residual $\hat{\varepsilon}_{it}$. In this case, there is no need to define a specific distribution for u and the estimator of the frontier constant term is consistent but biased and of uncertain efficiency.[23]

3. Technical Efficiency Measures

As above, we can consider with Richmond (1974) that the best measure of the average efficiency is given by $E(z)$ for $z = e^{-u}$. And we know that, for a specific distribution of u, we can define $E(z)$ with respect to μ_u and that we already have an estimator of μ_u based on the variance $\hat{\mu}_2(\varepsilon)$. Therefore, the average technical efficiency of observed productions can be calculated as follows:

$$E(z) = \begin{cases} \dfrac{1}{1 + [\hat{\mu}_2(\varepsilon)]^{1/2}} & \text{for an exponential distribution for } u \\ 2^{-\hat{\mu}_2(\varepsilon)} & \text{for a gamma distribution of } u \end{cases}$$

Another way to estimate the SCOPs' average efficiency in each sector is to compute the average of individual technical efficiencies weighted by the respective outputs. This approach, which Farrell (1957) initially considered with nonparametric frontiers, implies in our case that the frontiers are estimated with the MOLS method in order to obtain, for each observation, an efficiency degree smaller than or equal to 100%.[24]

Finally, van den Broeck, Forsund, Hjalmarsson, and Meeusen (1980) put forward a third measure of the average technical efficiency. They build an "average firm" on the basis of individual observations in a given industry. The efficiency of this firm is then calculated in reference to a deterministic frontier estimated either with a MOLS or a COLS method as long as this average firm does not stand above the frontier.

In their own empirical analysis, these authors define the average firm by the arithmetical averages of observed amounts of inputs and outputs. Such averages are precisely the ones we have for capitalist firms and the ones we have built for SCOPs in our comparative financial analysis (Defourny, 1986a, 1987). Thus, we shall pay particular attention to the results obtained with this third measure and to its significance with respect to the other possible measures.

4. The Results

The three average efficiency measures just described for deterministic frontiers have been calculated for each of the 14 industries in which most of the French SCOPs work. They are shown in Table 2.

Columns 3 and 4 show the sector average efficiency estimated by $E(z)$ for exponential and gamma distributions of the term u and thus refer to frontiers estimated with the COLS method. We see that, in all cases, the average degree of efficiency is smaller than the result obtained with a stochastic frontier, given the same distribution for u. It would be too easy to explain it by claiming that any difference via-à-vis the frontier is now imputed to technical inefficiency. We should not forget that many observations can be found well above the frontier and have an inflating effect on the average technical efficiency. Actually, the most relevant explanation consists in comparing the estimators $\hat{\mu}_u$ respectively obtained for stochastic and deterministic frontiers. We have seen that the variance of the residuals $\hat{\varepsilon}_{it}$ overestimates the u mean for a stochastic frontier (see note 12) whereas it estimates it correctly for a deterministic one. Since $E(z)$ is inversely linked to μ_u, the average efficiency thus estimated is therefore always smaller with the deterministic frontiers. Besides, it is not surprising at all to see that, when we use the same exponential distribution of u, the difference between both $E(z)$ values is smaller when the part of the residuals' variance attributable to the normal random term is itself smaller.[25]

Column 5 of Table 2 shows a second measure of the average technical efficiency with deterministic frontiers. As suggested by Farrell (1957), we have calculated for each sector an average, weighted by outputs, of individual technical efficiencies.[26] But an analysis of the results soon shows that such a measure is not appropriate, at least when the frontiers are estimated from individual observations with the MOLS method: the dependence via-à-vis the highest positive residual, that is, an extreme observation, is such that the average efficiency can fall under 30%.

The last column of Table 2 gives the most interesting average efficiency measure in a comparative perspective. As in our comparative financial analysis, we have first defined an average SCOP for each sector on a yearly basis. In order to do so, we used the arithmetic averages of the output and inputs of the observed individual firms. Along the lines of van den Broeck, Forsund, Hjalmarsson, and Meeusen (1980), we then calculated the average efficiency of each of those average firms on the basis of their respective frontiers. We shall note that, for these frontiers, the OLS constant term has been corrected by the estimated mean $\hat{\mu}_u$ and not by the highest positive residual. Moreover, we have only considered an exponential distribution of u since the efficiency of average firms was sometimes greater than 100% when we used a gamma distribution.[27] Finally, as a global estimation of the SCOPs' efficiency in a given sector, we have chosen the average, weighted by the number of observations, of efficiencies estimated for each of the average firms over nine years.[28]

These results have to be compared mainly with those shown in the third column of Table 2, that is, with the average efficiency defined by $E(z)$ for exactly identical frontiers (deterministic frontiers estimated with the COLS method on the basis of individual observations of SCOPs and under the assumption of an exponential distribution of u). These comparisons show that both measures give very similar results in some sectors (bricklaying, electricity, architecture, and consulting sectors) but that striking differences (sometimes more than 10%) may appear in one or two sectors (the industries related to printing or the telephone industry).

However, these differences can be seen as normal. Actually, except in extraordinary circumstances, the efficiency of an average firm (based on arithmetical averages) does not have to be equal to the average, though arithmetical, of individual efficiencies. Moreover, $E(z)$ is an average of individual efficiencies $e^{-u_{it}}$ but it is very specifically weighted: to each value $e^{-u_{it}}$ is associated a probability density defined by the distribution of e^{-u}, itself determined by the exponential distribution of u.[29]

The average technical efficiency of a group of firms can thus vary according to the approach we chose, even though the reference frontier remains unchanged. Therefore, we conclude that, for a comparative analysis of the efficiency of SCOPs and capitalist firms, it would not be appropriate to take into account, on one side, averages of individual efficiencies and, on the other, the efficiency of average firms. Hence, as we have only aggregate sectoral data, which allow us to build average capitalist firms in each industry,[30] we shall start working on the basis of identically defined average firms.

3. COMPARED TECHNICAL EFFICIENCY OF SCOPS AND CAPITALIST FIRMS

The previous section was mainly methodological: it made it possible to review various ways of making up and estimating the production frontier and the average efficiency of a group of firms. The empirical exercises simply illustrated the differences between these approaches and helped us in choosing the appropriate one for our comparative analysis of the efficiency of SCOPs and capitalist firms.

For these comparisons, we shall proceed stage by stage as in the financial analysis. First, we shall compare, in each sector, average firms representing all sizes of cooperative and capitalist units. Then, we shall divide these groups of firms into subgroups corresponding to size categories and we shall build average firms for each subgroup.

As in the previous section, we shall mainly refer to deterministic production frontiers, estimated on the basis of individual observations of SCOPs. A few problems may arise from this choice and they should be discussed before examining the results.

A. The Consequences of the Choice of Frontiers

We know that if we use deterministic frontiers we may mix up technical inefficiencies and the effects of measurement errors or the influence of external factors on the firms. Building average firms seems to reduce this risk even though it does not eliminate it. The measurement errors occurring in individual observations tend, indeed, to offset each other for average firms. Moreover, since the number of firms we are using in our analysis varies from year to year, there is less probability of a repetition of bias from one yearly average to the next. Finally, even though the distances separating the average firms from their respective frontiers do not reflect technical inefficiency only, we may probably assume that the interference of other phenomena has identical consequences on both types of firms and therefore does not alter the comparisons.

Another difficulty comes from the frontiers being estimated on the basis of cooperative productions only, without taking into account distinctive aspects of traditional firms. Indeed, it would have been much better to have individual observations on capitalist firms, comparable to the ones we have on SCOPs. Thus we could have built more general frontiers or even done what Marchand, Tulkens, and Pestieau (1984) suggested: to accept, at least for some industries, that both types of firms have different production frontiers that have to be estimated separately. In fact, we did use that method and we estimated distinct frontiers from capitalist and cooperative averages, calculated by size categories. But the much greater aggregation from which capitalist averages result means that the residuals with respect to the average production function are much weaker than on the cooperative side. The capitalist production frontier is thus built much closer to the average function, which automatically implies a much higher degree of efficiency than for the average of SCOPs.

Nevertheless, we shall try to evaluate the consequences of our choice. In our comparative analysis, we shall, indeed, examine to what extent our results change when we calculate the efficiency of average firms by referring to frontiers estimated on the basis of the capitalist averages only and not from individual cooperative observations.

B. Comparisons without Any Size Distinction

The two first columns of Table 3 give the average degree of technical efficiency of average cooperative and capitalist firms, built for each sector without making any size distinction. To obtain these results, we have followed the same method used in the preceding section: We first calculated the technical efficiency of average firms for each year, with a sector frontier

Table 3. Comparison of Technical Efficiencies of Average Firms of All Sizes

	Efficiency (%) of the average firm with a cooperative frontier		*Efficiency (%) of the average firm with a capitalist frontier*		*Factor coefficients for a Cobb–Douglas frontier*				*K/L (in thousands of 1970 FF)*	
					Cooperative frontier		*Capitalist frontier*			
	SCOP	*Sector*[a]	*SCOP*	*Sector*[a]	ln *K*	ln *L*	ln *K*	ln *L*	*SCOP*	*Sector*
Carpentry	77.1	78.2	81.6	96.0	0.11[b]	0.89	0.59	0.51	10.0	10.1
Bricklaying	80.6	80.8	94.4	82.6	0.05	1.01	0.13	0.84	8.6	11.4
Painting	73.5	74.5	83.2	84.6	0.13	0.86	0.18	0.84	3.9	6.3
Public works	84.8	64.6	74.8	74.5	0.20[b]	0.78	0.01	0.93	9.3	24.2
Plumbing	76.0	67.3	58.0	55.6	0.15	0.76	0.01	0.94	5.6	7.9
Electricity	69.6	68.3	82.1	78.7	−0.04[b]	1.33	0.03	1.00	8.0	9.1
Printing	70.0	65.7	94.9	88.8	0.20[b]	0.95	0.08	0.92	13.6	14.8
Related to printing	64.9	48.1	95.7	62.7	0.36[b]	0.52	0.01	0.95	16.5	13.2
Metal construction	73.7	66.6	93.1	85.0	0.05[b]	1.05	0.05	1.01	21.1	15.5
Sheet metal	76.6	91.7	88.0	93.0	0.06	0.99	0.32	0.69	8.9	18.7
Furniture	81.0	86.1	95.2	86.1	0.04[b]	1.04	0.39	0.64	9.9	12.7
Telephone	75.9	63.3	93.6	85.2	0.33	0.62	0.03	1.02	16.9	18.1
Architecture	80.3	76.7	77.4	76.6	0.08	1.01	0.02	0.97	8.5	15.6
Consulting	65.0	42.0	96.4	43.1	0.14	1.14	0.02	0.97	8.7	23.9

[a]Results for the whole sector, which are taken as representative of capitalist firms' efficiency.
[b]Sector for which the cooperative production frontier used for the efficiency measurement has a translog or a CES form (Kmenta version).

estimated by COLS (with an exponential distribution for the term u) on the basis of individual cooperative observations. We then calculated an average over the nine years, weighted by the number of firms involved.

The technical efficiency we get is greater on the cooperative side in nine sectors. On the other hand, it is almost identical for both types of firms in the bricklaying industry and is higher on the capitalist side in four sectors: carpentry, painting (though the difference there is only $\sim 1\%$), and sheet metal. It is interesting to note that these results are generally similar to those obtained in the financial analysis of labor productivity (Defourny, 1987).

As we have said, we have also computed the average efficiency by estimating sector frontiers from the capitalist averages only and by using all available data: not only all-size yearly averages over the 1971–1979 period but also averages calculated for six size categories in the year 1979.

We see two fundamental things from the results shown in Table 3, columns 3 and 4: on the one hand, the difference between cooperative and capitalist efficiencies often varies very much from one type of frontier to the other but, on the other hand, the sign of the difference always remains unchanged except in one sector (the furniture industry).

To explain the variations of the difference between cooperative and captialist efficiencies, we shall use, in the right half of Table 3, the estimated coefficients of capital and labor factors for Cobb–Douglas sector frontiers. With capitalist averages, the Cobb–Douglas form must, indeed, be used for all sectoral frontiers.[31] With regard to frontiers estimated from individual cooperative observations, we have seen that some of them have a translog or a CES (Kmenta's version) form but we have checked that the degree of efficiency does not vary much when we choose a Cobb–Douglas specification.

This presentation makes the comparisons between both types of frontier much simpler and leads us to distinguish four possible situations:

1. First, when the coefficients of factors K and L do not vary much from one frontier to the other, the difference between the two average efficiencies logically remains very stable. This is effectively the case in painting, metal construction, and architecture.

2. On the other hand, if, going from the cooperative to the capitalist frontier, the coefficient of factor K decreases significantly and the coefficient of factor L increases, the difference between average efficiencies clearly changes in favor of the firms that have the highest capital–labor ratio.[32] By computing this ratio (see Table 3), we can check, indeed, that the most capital-intensive average firm is the capitalist one in plumbing, telephone, and public works, but it is the cooperative one in the industries related to printing.

3. The third situation is exactly the opposite of the preceding one and can be found in the carpentry, the bricklaying, the electricity, the furniture, the sheet metal, and consulting sectors. In this case, the difference changes to the advantage of more labor-intensive firms, that is, the average SCOP for five out of six of the aforesaid sectors. On the other hand, in the carpentry industry, the K/L ratio shows identical capital intensity on both sides. In order to explain why SCOPs stand well behind capitalist firms, we must examine the returns to scale: they remain constant with the cooperative frontier but they increase noticeably with the capitalist frontier. And, in this sector, the average SCOP is five times bigger than the average capitalist firm. Hence the distances with respect to the frontier are evolving to the detriment of the SCOP.[33]

4. The last situation is found in the printing industry, where both coefficients of the frontier function change in the same direction. The difference in the returns to scale is also important here but both average firms have practically the same size and the same capital intensity. This explains why the difference between the average efficiencies does not change much.

Before going on with the analysis by size categories, we shall note that, beyond the results showing identical directions for 13 out of 14 sectors, both types of frontiers lead to precise conclusions for most sectors: on the one hand they show a very clear inferiority of SCOPs in the sheet metal industry and a very slight one in the painting sector; on the other hand they show a cooperative superiority that is rather slight in architecture but very significant in printing, industries related to printing, metal construction, telephone, and consulting sectors. Let us recall, however, that we are dealing here with average tendencies given by an all-size analysis.

C. Comparisons by Size Categories

In the financial analysis, we had found that the firms' size was a key factor of the SCOPs' relative economic performance. It may be the same for technical efficiency.

As far as the size of the firms compared is concerned, we will develop our analysis in two directions. First, from the disaggregated capitalist averages, which are only available for 1979, we will try to reconstitute averages per size for the previous years. Second, as SCOPs are mainly small- or medium-sized enterprises (SMEs), we will use five or six size categories, wih four of them allowing fine distinctions among firms that employ less than 100 workers.

1. *Projection of Averages per Size Category for 1971–1978*

Within each sector, we are confronted with the following problem. We know the values V_{i79}, K_{i79}, L_{i79}, and N_{i79}, which, respectively, represent added value, net fixed assets, number of workers, and number of individual firms we cover for each average capitalist firm of the ith size group ($i = 1, 2, \ldots, 6$) for 1979. We also have the values V_t, K_t, L_t, and N_t (with $t = 1971, \ldots, 1979$), the first three variables representing all-size averages and the fourth being the total number of firms in the sector. Our aim is to reconstitute around all-size average firms defined by V_t, K_t, L_t, and N_t ($t = 1971, \ldots, 1978$), average firms per size category (defined by V_{it}, K_{it}, L_{it}, and N_{it}) on the basis of the distribution of averages V_{i79}, K_{i79}, and L_{i79} around all-size averages V_{79}, K_{79}, L_{79} as well as on the basis of the ratios between the N_{i79} and N_{79}.

It is no trouble at all to project the values N_{it}, for the most natural approach consists in supposing that the relative importance of each size category is constant from year to year. Therefore, we defined the N_{it} so that $N_{it}/N_t = N_{i79}/N_{79}$ ($t = 1971, \ldots, 1978$).

We have tried different ways of projecting the other variables to choose finally the one that best combines realism and maximum exploitation of information. First of all, we set $L_{it} = L_{i79}$ in order to have, as in 1979, an average capitalist firm in each group defined by the number of workers.[34]

Then we calculate K_{it} in such a way that, for each year, the ratio K_{it}/L_{it} will be separated from K_t/L_t by the multiplying factor that separates K_{i79}/L_{i79} from K_{79}/L_{79}. In other words, we try to reproduce the differentiation of the 1979 average firms, expressed in capital intensity.[35]

Finally, each V_{it} value is determined by the corresponding K_{it} and L_{it} values, through a production function. The latter is estimated on the basis of all available capitalist averages for the sector (all-size yearly averages for 1971–1979 and per size averages for 1979). For each sector, we use a Cobb–Douglas function whose estimated coefficients of the factors have already been given in Table 3, columns 7 and 8.[36]

2. *Results*

The technical efficiency of each capitalist firm thus defined and of each average SCOP has been calculated as in the all-size analysis. In other words, the reference sector functions are those already estimated on the basis of individual observations regarding SCOPs (see Table 1). The results that we finally obtained are, for each size category, average efficiencies over the 1971–1979 period, weighted by the number of firms we have covered. These average efficiencies per size are shown in Table 4. To make the reading and the interpretation of these results straightforward, we also present them graphically in Figures 1–14.

The analysis of the graphs shows, first of all, a clear coherence in the evolution of the SCOPs' average relative efficiency. Indeed, despite very few observations in some categories and the rather artificial feature of average capitalist firms over the 1971–1978 period, we do not observe, in any sector, continuous shifts of the cooperative efficiency curve from one to the other side of the curve relative to capitalist firms.

Table 4. Comparison of Average Technical Efficiencies by Size Categories

	SCOP	*Sector*
Carpentry		
1–9	79.0	79.8
10–19	81.7	76.0
20–49	80.0	79.2
50–99	81.6	88.9
100–199	75.2	89.2
200–499	82.6	94.4
Bricklaying		
1–9	80.7	96.8
10–19	79.1	83.7
20–49	79.9	78.1
50–99	87.0	71.8
100–199	79.9	68.7
200–499	73.2	64.2
Painting		
1–9	80.0	73.8
10–19	76.1	73.4
20–49	76.3	74.7
50–99	94.1	76.4
100–199	80.9	77.3
200–499	61.4	79.1
Public works		
1–9	76.1	81.2
10–19	83.5	85.9
20–49	88.4	86.8
50–99	90.7	84.1
100–199	83.1	76.8
200–499	72.0	70.0
Plumbing		
1–9	61.1	62.7
10–19	84.9	70.5
20–49	77.3	73.4
50–99	88.9	72.6
100–199	78.3	68.1
20–499	80.1	70.7
Electricity		
1–9	91.4	92.7
10–19	93.2	90.2
20–49	69.[illegible]	68.4
50–99	70.1	65.4
100–199	77.8	92.6
Printing		
1–9	76.5	87.5
10–19	67.2	74.9
20–49	70.0	65.7
50–99	66.5	62.1
100–199	91.7	67.1
200–499	87.9	70.4
Related to printing		
1–9	95.4	89.8
10–19	76.8	56.0
20–49	81.3	52.0
50–99	71.9	72.6
100–199	80.7	94.3
Metal construction		
1–9	70.2	72.6
10–19	80.4	70.0
20–49	75.6	68.4
50–99	76.0	64.9
100–199	83.3	64.7
200–499	75.2	61.1
Sheet metal		
1–9	68.3	95.7
10–19	78.5	83.2
20–49	74.2	81.6
50–99	54.9	82.0
100–199	65.2	87.5
Furniture		
1–9	68.6	60.7
10–19	87.2	72.4
20–49	72.6	71.5
50–99	73.4	77.0
100–199	75.5	85.5
Telephone		
1–9	66.1	73.2
10–19	81.1	65.6
20–49	76.1	63.9
50–99	93.6	63.1
⩽ 100[a]	98.7	76.7
Architecture		
1–9	78.6	79.8
10–19	83.5	72.1
20–49	78.2	69.7
50–99	72.9	68.2
Consulting		
1–9	64.4	45.7
10–19	68.0	41.8
10–49	56.9	40.4

[a] This category makes it possible to include the biggest French SCOP.

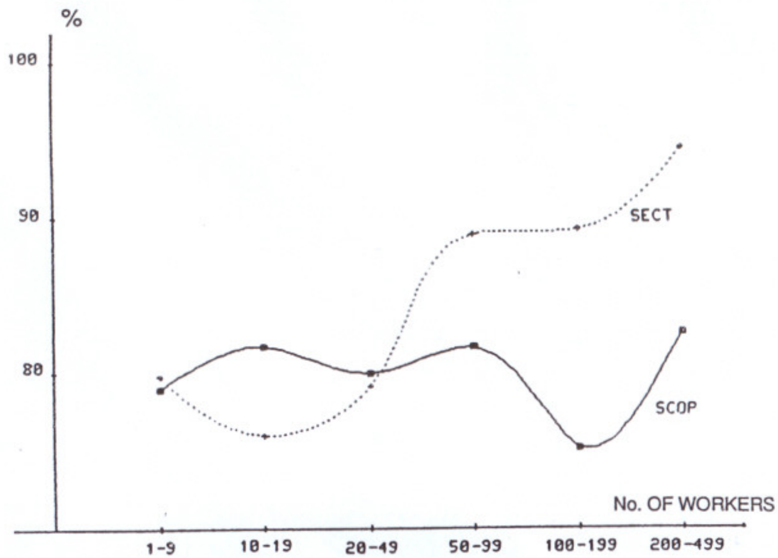

Figure 1. Carpentry—comparison of average technical efficiencies by size categories.

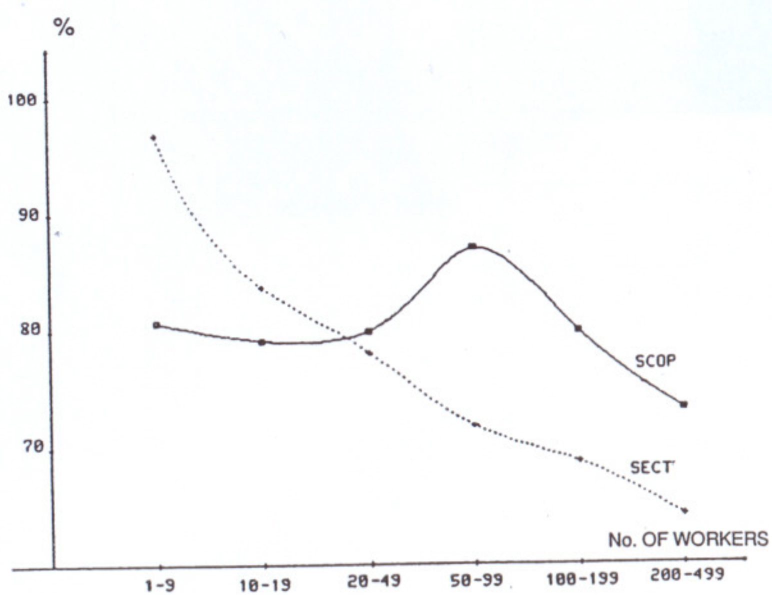

Figure 2. Bricklaying—comparison of average technical efficiencies by size categories.

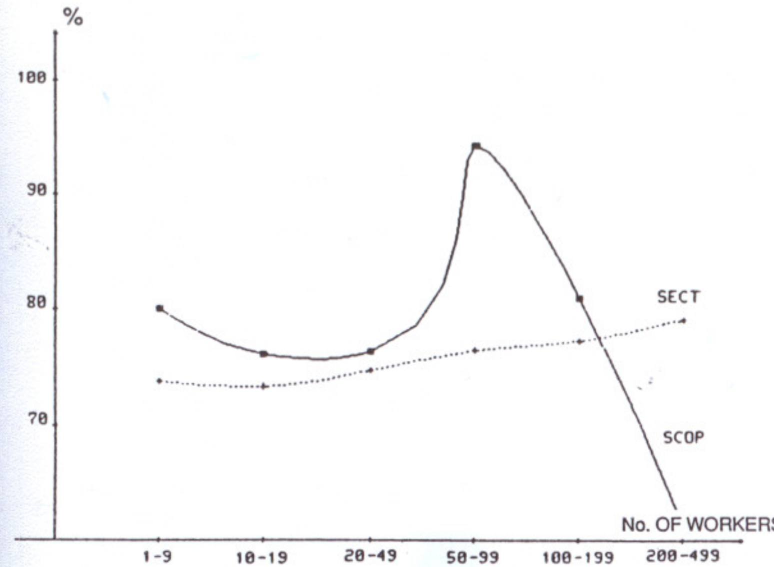

Figure 3. Painting—comparison of average technical efficiencies by size categories.

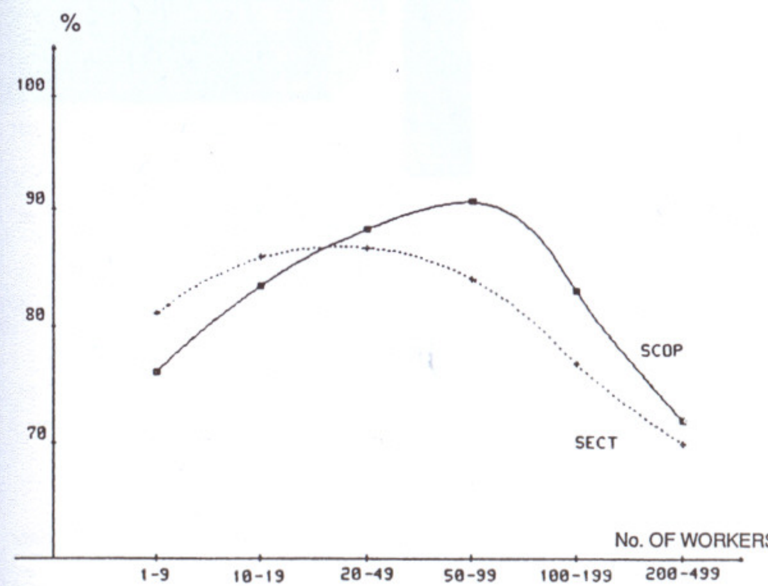

Figure 4. Public Works—comparison of average technical efficiencies by size categories.

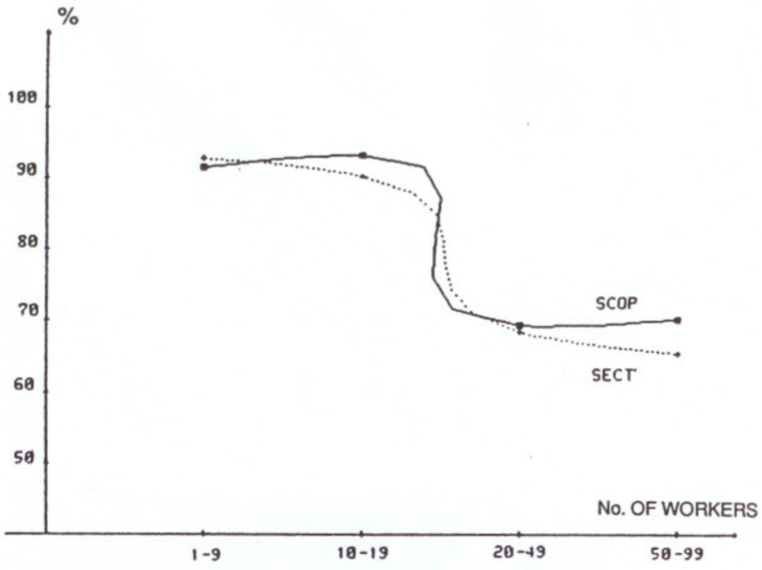

Figure 5. Electricity—comparison of average technical efficiencies by size categories.

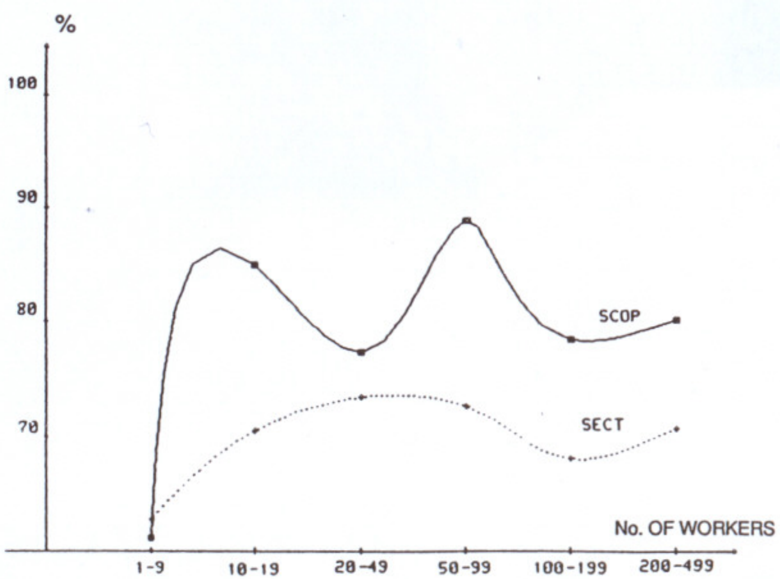

Figure 6. Plumbing—comparison of average technical efficiencies by size categories.

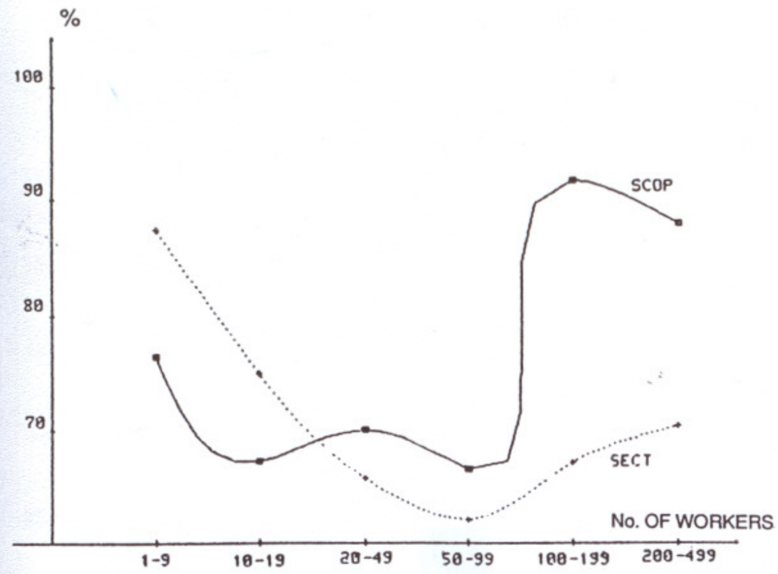

Figure 7. Printing—comparison of average technical efficiencies by size categories.

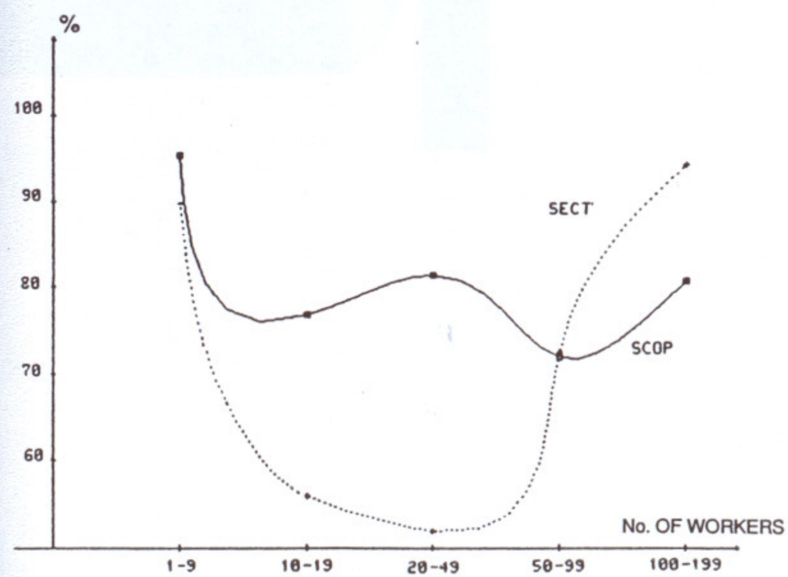

Figure 8. Industries related to printing—comparison of average technical efficiencies by size categories.

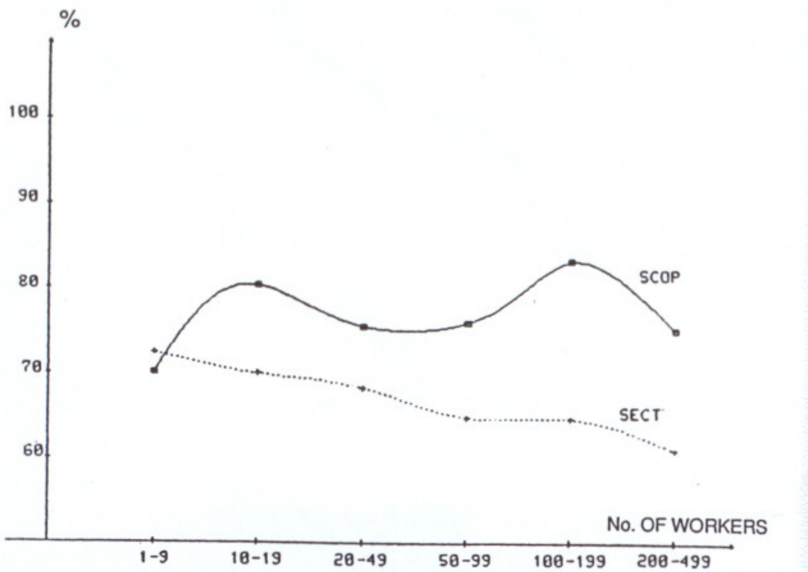

Figure 9. Metal construction—comparison of average technical efficiencies by size categories.

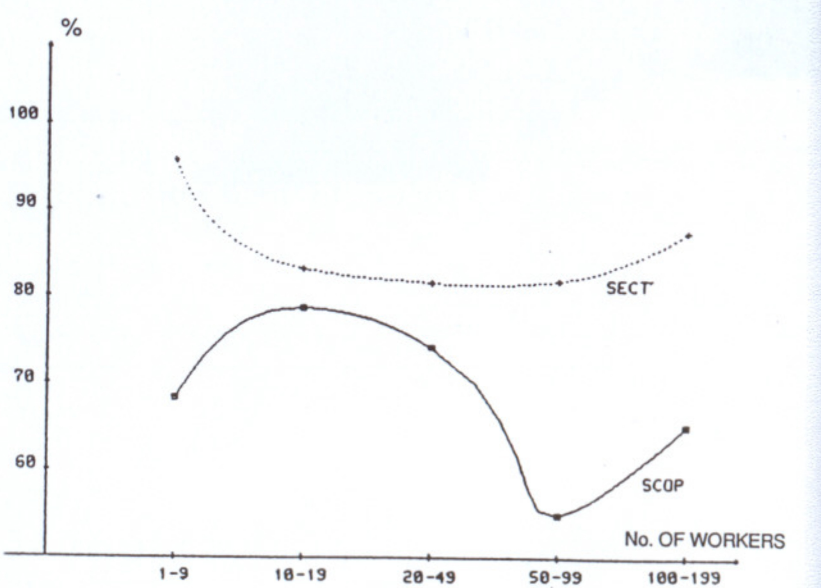

Figure 10. Sheet metal—comparison of average technical efficiencies by size categories.

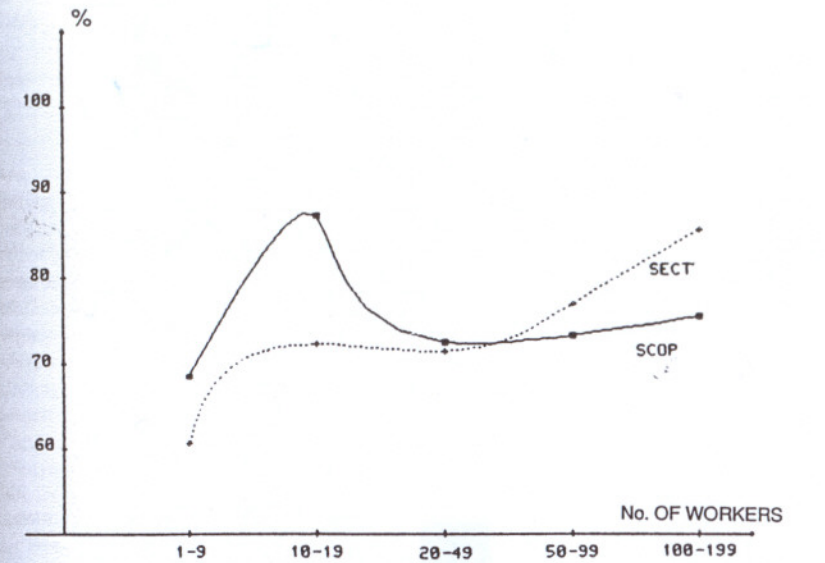

Figure 11. Furniture—comparison of average technical efficiencies by size categories.

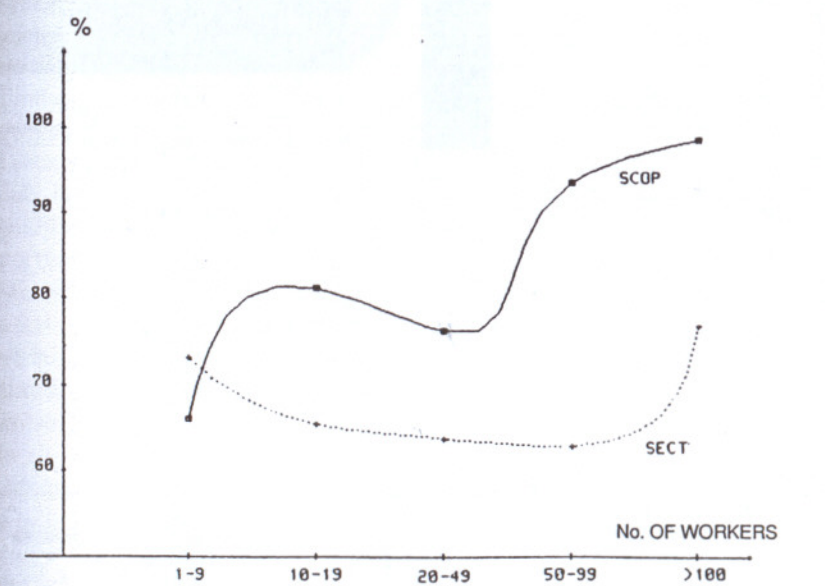

Figure 12. Telephone—comparison of average technical efficiencies by size categories.

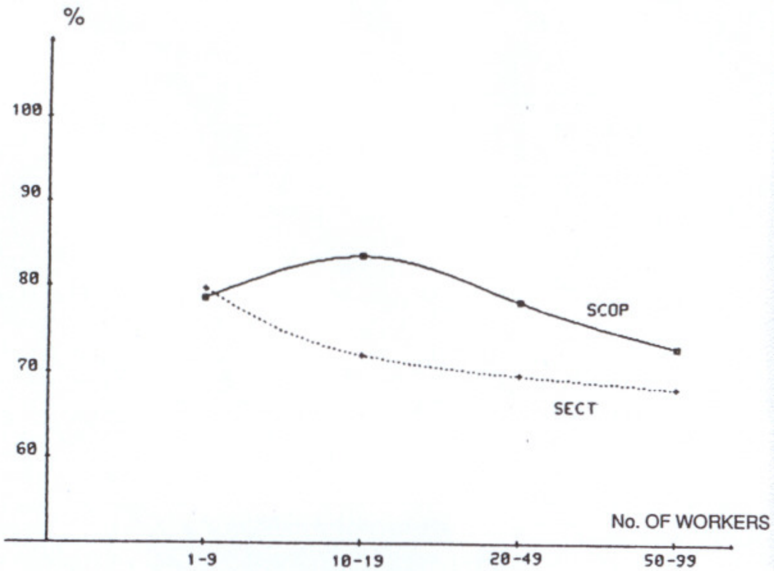

Figure 13. Architecture—comparison of average technical efficiencies by size categories.

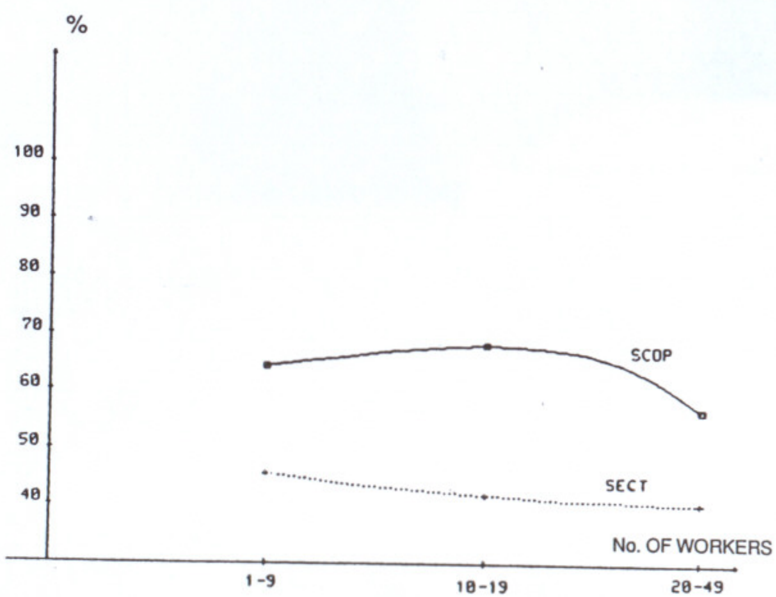

Figure 14. Consulting—comparison of average technical efficiencies by size categories.

Table 5. Evolution of the SCOP Relative Efficiency with Respect to Their Size

Sectors	*Number of Workers*					
	1–9	10–19	20–49	50–99	100–199	200–499
Painting	+	+	[a]	+	+	−
Furniture	+	+	[a]	−	−	
Related to printing	+	+	+	[a]	−	
Consulting	+	+	+			
Metal construction	−	+	+	+	+	+
Telephone	−	+	+	+		
Architecture	[a]	+	+	+		
Plumbing	[a]	+	+	+	+	+
Electricity	[a]	+	[a]	+	+	
Carpentry	[a]	+	[a]	−	−	−
Bricklaying	−	−	+	+	+	+
Public works	−	−	+	+	+	+
Printing	−	−	+	+	+	+
Sheet metal	−	−	−	−	−	−

[a]No more than a 2% difference.

Even though it is important to interpret the efficiency differentials with caution, the results we have ontained enrich our analysis considerably.[38] Moreover, they are well summed up in Table 5 which only shows the sign of efficiency differentials between cooperative and capitalist firms. A positive (negative) sign indicates a higher (lower) efficiency of SCOPs.

First of all, this table confirms and at the same time qualifies the pattern shown by the financial analysis as to the links existing between the size and the economic performance of SCOPs. For small-sized SCOPs, the situation is only favorable in the first four sectors, that is, sectors that are not very capital-intensive or that are heterogeneous enough to offer labor-intensive opportunities in which it is possible to work with very low amounts of capital. When we compare the average capital–labor ratios of the different sectors (see last column of Table 3), we find, indeed, that the painting industry is the most labor intensive and so is the furniture industry outside the building sector. Industries related to printing and consulting include very diverse activities that, in some cases, require very low investment.[39]

In all the other sectors, small-sized SCOPs stand behind their capitalist counterparts as far as technical efficiency is concerned. This is probably due to a lack of equity, to a more limited accessibility to loans, or to a much too small profitability[40] but the situation usually comes back to normal as soon as the firm grows and goes beyond a critical point (more or less ten workers). Yet the critical size is higher in bricklaying and in public works, both being the most capital-intensive industries in the building sector. It is higher as well in printing, which is a rather homogeneous sector requiring, from the start, substantial investments. Finally, in the sheet metal industry, Figure 10 clearly shows an improvement in the relative efficiency of SCOPs for the second and third size categories. However, the situation always remains unfavorable for SCOPs in a sector that is precisely the most capital-intensive one among industrial activities.

However, we may wonder why SCOPs have such a better relative efficiency in other industrial sectors (metal construction and telephone industries). These sectors also require substantial investment and do not seem to be less homogeneous than the sheet metal industry. We can only refer to the results of the financial analysis: unlike the SCOPs working in these two sectors, the sheet metal industry SCOPs, even with a great number of workers, sorely lack equity and do not counterbalance it with an increased accessibility to loans. Thus, they are not able to invest as they should in order to compete with the other firms of the sector. In any case, for industries that are at first sight comparable, these differences of behavior and performance have one thing to their credit: beyond the average tendencies we are trying to bring out, they emphasize how diverse cooperative realities are.

However, a few average tendencies are particularly striking when we examine the third column of Table 5: in the category of firms with 20–49 workers, the SCOPs' average technical efficiency is, in 13 out of 14 sectors, greater than the efficiency of the other firms. The importance of such a result is even greater since we know that this is the main category in all the industries except for the intellectual services and the industries related to printing.[41] Globally, it represents, indeed, 718 out of 2050 individual observations on SCOPs.[42]

Is that greater technical efficiency of SCOP generated by workers' participation? Would such an impact of workers' participation also exist but be offset by the lack of capital in small SCOPs? Or would workers' participation have a weaker effect on productivity in the latter due to a certain "excess of democracy," that is, a willingness to allow everybody to decide on everything, while its impact would be stronger when, as in medium-sized SCOPs, it is exerted in a more structured way and with more power delegated?

We are unable to answer all these questions precisely but we have explored elsewhere the relation between SCOPs' productivity and workers' involvement at different levels. In an early study (Defourny et al., 1985) based on data for SCOPs in 1978 and 1979 and on the estimation of production functions augmented by various measures of workers' participation, value added was found to be an increasing function of participation in profits and, to a lesser extent, in collective membership and in ownership, even when a wide assortment of enterprise-specific and environmental factors were taken into account. More recently (Defourny, 1987), we developed the same kind

of analysis on a broader basis: we used our whole data set covering ten years and including data on nonparticipatory capitalist enterprises and we worked on 14 industries instead of 6. Moreover, indicators of workers' participation were partly defined in a different way, referring to collective membership, profit-sharing, individual and collective ownership of capital, and two forms of workers' loans. We also specified augmented production functions in such a way as to allow for "embodied" as well as "disembodied" effects of participation. The main results of the estimation of these production functions indicate that workers' participation generally has a positive global effect on the enterprise productivity although this effect is rather limited, most often from 3 to 5%. They also show that workers' individual participation in capital stakes, profit shares, and enterprise financing through midterm individual loans are the most effective channels through which participation influences productivity. Moreover, these findings are very robust, surviving tests between alternative specifications of technology, for reverse causality, for simultaneous-equations bias, and for multicollinearity between the participatory variables.

Finally, coming back to Table 5, we see another interesting result regarding the three categories that group together the biggest cooperative firms. Table 5 shows that beyond 50 workers, the SCOPs' technical efficiency is most often greater than in the other firms, though it may also become smaller than the sector average. This happens in the carpentry and the furniture sectors as well as in the industries related to printing. We also observe a similar evolution in the painting sector when a firm has more than 200 workers but we found that this upper category includes only one firm. Besides, both the bad relative efficiency of that SCOP and its great weight clearly explain why the painting industry seemed rather unfavorable to SCOPs in an all-size analysis. But, thanks to a subtler analysis, we now see that this very labor-intensive activity is, on the contrary, one of the easiest for producer cooperatives.

3. Conclusions

Within the category of parametric production frontiers estimated with inferential methods, we have seen that several approaches may be used for the conception and the empirical building of such frontiers. Since the stochastic frontiers represent the most relevant approach at a theoretical level, we have exploited that method as much as possible and we have estimated an average degree of technical efficiency for all SCOPs of each sector.

However, to achieve a true comparative analysis of the efficiency of cooperative and capitalist firms, we had to use deterministic frontiers. After having considered three possible methods to estimate the average efficiency, we had to choose the most appropriate, given our data. Finally, the frontier estimation in itself was based on the observations of SCOPs alone and we found that this option mostly had an effect on the value of the efficiency differentials but almost none on their sign.

These remarks underline the relativity of our efficiency study. They also show that each choice has been made in order to get the most out of the available information and to give as rigorous a basis as possible to our comparisons. In brief, we can say that our analysis has highlighted great differences among SCOPs, when we compare their technical efficiency to that of their capitalist counterparts, the firm's size and the type of activity being two main differentiation factors.

Medium-sized SCOPs, particularly those employing 20–49 workers, almost always have a rather greater technical efficiency than their capitalist counterparts. Another briefly summarized study based on the same data indicates that this superiority is probably due, at least partly, to workers' participation. On the other hand, very small SCOPs are usually found in the opposite situation, although this tendency to have a lower productivity is not to be generalized. This inferiority is linked to a very small amount of fixed assets and it is not found in very labor-intensive sectors, where SCOPs can easily work with limited material means. In that, the technical efficiency analysis, though it gives a different point of view, fully confirms the main results of our previous financial ratios study.

Finally, the efficiency analysis shows that, although SCOPs often have a better productivity than capitalist firms, they lose this advantage in some industries once they reach a certain size. This evolution might be seen as an almost inevitable weakening of workers' participation when the firm grows. But such an explanation would need to be confirmed by further research.

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NOTES

1. We have surveyed these works in Defourny (1987, pp. 51–72). Some other researchers have tried to identify statistically significant relations between the economic performance of self-managed firms and indicators of workers' participation or they have compared economic results of firms before and after their conversion into self-managed enterprises. But these analyses do not compare firms of two kinds operating at the same time in the same activity.

2. The main survey is the one carried out by Forsund, Lovell, and Schmidt (1980). On that basis, some syntheses have also been made by d'Aspremont (1984, pp. 33–49), Deprins (1985, pp. 3–12), and Thiry (1985, pp. 4–12).

3. Forsund, Lovell, and Schmidt (1980, p. 20) stress that, in practice, this distinction is not important since both notions converge asymptotically.

4. In this case, the set of possible productions can be said to be convex (for instance, Farrell, 1957) or nonconvex (Deprins et al., 1984).

5. In addition to their simple mathematical expression, a great advantage of the parametric frontiers is their easy adaptability to nonconstant returns to scale.

6. Stochastic frontiers are also called composed-error frontiers. Aigner, Lovell, and Schmidt (1977) as well as Meusen and van den Broeck (1977) were the first to develop these models.

7. We assume that, for a given sector, the frontier can only shift in parallel to itself from one year to the next.

8. The proposals of the three authors are meant for deterministic frontiers, but they hold for stochastic frontiers as well since u is not dependent on v.

9. (a) The exponential distribution can be defined as follows:

$$g(u) = (1/\sigma_u)\exp(-u/\sigma_u)$$

and its first three moments are

$$E(u) = \sigma_u, \qquad V(u) = \sigma_u^2, \qquad \mu_3(u) = 2\sigma_u^3$$

The gamma distribution can be written

$$g(u) = [\Gamma(\sigma_u)]^{-1}(u)^{\sigma_u - 1}\exp(-u)$$

with its first moments being

$$E(u) = V(u) = \sigma_u, \qquad \mu_3(u) = 2\sigma_u$$

(b) Those are the two distributions most often considered. The test suggested by Lee (1983) to make a choice among various possible distributions would be another approach, but this test is particularly cumbersome.

10. In fact, Richmond's proposal refers to deterministic frontiers but it can be applied to stochastic ones as well.

11. Instead of the COLS, we could use the ML method. With the latter, however, an already mentioned problem arises: the estimators $\hat{\alpha}_i$ are dependent on the distribution chosen for u. Besides, Olson, Schmidt, and Waldman (1980) have compared both techniques with the Monte Carlo method. They conclude that the possible gain of efficiency obtained with the ML method is not enough to consider it more interesting than the COLS method, whose application is particularly simple.

12. We have to use the third moment because, by assumption, the mean of ε and its variance are not equal to the u mean and variance. Indeed, $E(\varepsilon) = 0$, whereas $E(u) \geqslant 0$; and

$$V(\varepsilon) = V(u) + V(v)$$

with $V(v) = \sigma_v^2$. On the other hand,

$$\mu_3(\varepsilon) = E[\varepsilon - E(\varepsilon)]^3 = E\{\mu_u - u + v - [\mu_u - E(u) + E(v)]\}^3 = -E[u - E(u)]^3 = -\mu_3(u)$$

13. This link can easily be found with the formulas given in note 9. For an exponential distribution $E(u) = [\mu_3(u)/2]^{1/3}$. For a gamma distribution, $E(u) = \mu_3(u)/2$.

14. If we estimated the u mean from other ε moments, we would get, in most cases, different values for $\hat{\mu}_u$.

15. This will occur each time that $\hat{\varepsilon}_{it} > \hat{\mu}_u$.

16. In this, he is following a suggestion of Afrait (1972), which is to measure the technical efficiency degree of the ith firm at time t by $Y_{it}^0/f(X_{it}) = z_{it}$.

17. If we note by $Y^x = f(X)$ the points of a deterministic frontier and by $Y^x = f(X)e^v$ the points of a stochastic one, respectively, then it is obvious that in both cases we have $E(Y^0/Y^x) = E(e^{-u})$.
18. Here, $b_1^{1/2} = \mu_3/\mu_2^{3/2}$.
19. White and MacDonald (1980) show that this test is asymptotically valid when we use the residuals of OLS.
20. At least, this is the case if, as for our ten frontiers, $\hat{\mu}_3(\varepsilon)$ is negative and greater than -1. Indeed, if $-1 < \hat{\mu}_3(\varepsilon) < 0$, $\hat{\mu}_u$ (exponential) $= -[\hat{\mu}_3(\varepsilon)/2]^{1/3} > -\hat{\mu}_3(\varepsilon)/2 = \hat{\mu}_u$ (gamma).
21. At least if we keep the same frontier for all subgroups.
22. $\mu_2(\varepsilon)$ or $V(\varepsilon) = V(\mu_u - u) = V(u)$.
23. See Greene (1980).
24. van den Broeck, Forsund, Hjalmarsson, and Meeusen (1980) note that, in terms of potential increase of the output, the result of such a weighting cannot be as clearly interpreted as the technical efficiency degree calculated for an individual observation.
25. There is no reason, however, for this relation always to be true.
26. Individual efficiencies refer to the estimates made for each observation but not to the ones made for each firm on the basis of various observations.
27. Since $\mu_2(\varepsilon)$ is always smaller than one, the correction μ_u is always much higher for an exponential than for a gamma distribution of u. Indeed, if $\hat{\mu}_2(\varepsilon) < 1$, $\hat{\mu}_u$ (exponential) $= [\hat{\mu}_2(\varepsilon)]^{1/2} > \hat{\mu}_2(\varepsilon) = \hat{\mu}_u$ (gamma).
28. We have not measured the efficiency of a single average SCOP based on the nine years because it was easier and more logical to calculate yearly average efficiencies first, since the frontiers of each activity had yearly dummy variables.
29. We have seen that this weighting leads to the result $E(e^{-u}) = 1/(1 + \mu_u)$. With the estimate based on the average firms, though, the distribution of e^{-u} only takes place in the correction of the OLS constant term, that is, in the frontier estimate.
30. We assume that noncaptialist firms do not represent a significant part of these industries. For a detailed description of the data, see Defourny (1986a, 1987). Here we just want to stress two of their characteristics: they cover most of the firms in each industry and industry definitions correspond very precisely to those used for SCOP classifications.
31. This form is usually all the more appropriate for a production function when the data used for its estimation are strongly aggregated.
32. From one efficiency estimation to the other, the average firms compared obviously remain the same, but their possible maximum productions, defined by the reference frontier function, change. Since the frontier has the form $\ln V = \alpha \ln K + \beta \ln L$, if α decreases and β increases, the difference between observed and maximum productions predicted by the frontier decreases more or increases less for the average firm whose labor factor is greater vis-à-vis the capital factor.
33. Indeed, if we go from constant returns to increasing returns, the possible maximum production, determined by the frontier function for the quantities of inputs of the average SCOP, increases more or decreases less than the possible maximum production corresponding to the inputs of the average capitalist firm.

Important differences in returns to scale can also be found in other sectors, but size differences are less obvious. For example, in the electricity sector, returns go from 0.97 to 1.29 but the average cooperative and capitalist firms, respectively, employ 49 and 35 workers.
34. Another method would consist in reproducing, between L_{it} and L_t, the difference (in absolute or relative terms) existing between L_{i79} and L_{79}. In this case, however, if we work in absolute terms, we sometimes get negative L_{it}, whereas in relative terms there is no guarantee that L_{it} would be found within the range of L values defining the group i.

35. Another solution would be to suppose a ratio K_{it}/L_{it} that remains constant for the same group year after year and is determined by K_{i79}/L_{i79}. It is not as interesting as the one we chose, for it does not take into account the information given by the global average firm of each year (K_t/L_t).
36. The two possible alternatives would have been to use production functions esstimated from observations on SCOPs or to reproduce, between V_{it} and V_t, the relative difference existing between V_{i79} and V_{79}. In the first case though, all average capitalist firms of one sector, except the 1979 ones, would have had an identical degree of technical efficiency. With regard to the second alternative, no clear economic interpretation can be made from it.
37. Average cooperative firms of each category have been built, as before, by arithmetical averages on the individual observations of the subgroup concerned.
38. Since the frontiers are estimated on the basis of cooperative productions only, we must not consider the values of the differentials as being very important. For this matter, see the all-size analysis.
39. Industries related to printing include graphic arts. The consulting sector deals with resistance estimates for a house as well as with the design of a production line for a factory.
40. See the results of the financial analysis (Defourny, 1987).
41. In architecture, most SCOPs have less than ten workers whereas the second category (10–19 persons) is most dominant in the consulting sector and in the industries related to printing.
42. The category employing 10–19 workers comes second with 476 observations.

REFERENCES

Afriat, S. N. (1972), "Efficiency Estimation of Production Functions," *International Economic Review* 13 (3): 568–598.
Aigner, D., Lovell, C. A. K., and Schmidt, P. (1977), "Formulation and Estimation of Stochastic Frontier Production Function Models," *Journal of Econometrics* 6(1): 21–37.
Camus, B., Ferre, T., Rousset, M., and Tamisier, M.-H. (1983), *SUSE: Système Unifié de Statistiques d'entreprises (Sources, méthodes et apports)*, Collections de l'INSEE, Series E, no. 86.
Christensen, L. R., Jorgenson, D. W., and Lau, L. J. (1973), "Transcendental Logarithmic Production Functions," *Review of Economics and Statistics* 55: 28–45.
Confederation Generale des SCOP (1980/1981), *Annuaire de la coopération ouvrière de production*, Paris.
d'Aspremont, A. (1984), "Une mesure générale d'efficacité au sens de Farell: Application au cas de la STIB," Ph.D. thesis, Catholic University of Louvain.
Defourny, J. (1986a), "Une analyse financière comparative des coopératives de travailleurs et des entreprises capitalistes en France," *Annals of Public and Cooperative Economy* 57(1): 55–78.
Defourny, J. (ed.) (1986b), "The Economic Performance of Self-Managed Firms. A Comparative Perspective," Special Issue, *Annals of Public and Cooperative Economy* 57(1).
Defourny, J. (1987) "La performance économique comparée des coopératives de travailleurs. Le cas des SCOP françaises," Ph.D. thesis, University of Liege. (Partly published under the title *Démocratic coopérative et Efficacité économique*, De Boeck, Bruxelles, 1990.)
Defourny, J., Estrin, S., and Jones, D. C. (1985), "The Effects of Workers' Participation on Enterprise Performance. Empirical Evidence from French Cooperatives," *International Journal of Industrial Organization* 3: 197–217.
Demoustier, D. (1985), "Les SCOP dans l'économie française," *Revue de l'économie sociale* 3: 67–72.

Deprins, D. (1985), *Estimations de mesures d'efficacité technique: La problèmatique et les différentes approches*, Séminaire de mathématiques appliquées aux sciences humaines, Cahier no. 8503, Facultés universitaires St.-Louis, Bruxelles.

Deprins, D., Simar, L., and Tulkens, H. (1984), "Measuring Labor-inefficiency in Post-Offices," in M. Marchand et al. (eds), *The Performance of Public Enterprises: Concepts and Measurements*, pp. 243–267, North-Holland, Amsterdam.

Farrell, M. J. (1957), "The Measurement of Productive Efficiency," *Journal of the Royal Statistical Society* 120 (Series A): 253–281.

Forsund, F. R., Lovell, C. A. K., and Schmidt, P. (1980), "A Survey of Frontier Production Functions and of Their Relationship to Efficiency Measurement," *Journal of Econometrics* 13: 5–25.

Greene, W. H. (1980), "Maximum Likelihood Estimation of Econometric Frontier Functions," *Journal of Econometrics* 13: 5–25.

Insee (1976a–1980), *Les comptes intermédiaires des entreprises en 1971, 1972, 1973, 1974, 1975, 1976,* Collections de l'INSEE, Series E, no. 34 (microfiches for years 1977–1979).

Jones, D. C. and Svejnar, J. (eds.), (1982), *Participatory and Self-Managed Firms*, Lexington Books, Lexington, MA.

Jones, D. C. and Svejnar, J. (eds.) (1985), *Advances in the Economic Analysis of Participatory and Labor-Managed Firms*, Vol. 1, JAI Press, Greenwich, CT.

Kmenta, J. (1967), "On the Estimation of the CES Production Function," *International Economic Review* 8: 180–189.

Lee, L.-F. (1983), "A Test for Distributional Assumptions for the Stochastic Frontier Functions," *Journal of Econometrics* 22: 245–267.

Marchand, M., Pestieau, P., and Tulkens, H. (1984), "The Performance of Public Enterprises: Normative, Positive and Empirical Issues," in M. Marchand et al., *The Performance of Public Enterprises: Concepts and Measurement*, pp. 3–42, North-Holland, Amsterdam.

Meeusen, W. and Van den Broeck, J. (1977), "Efficiency from Cobb–Douglas Production Functions with Composed Error," *International Economic Review* 18: 435–444.

Olson, J.-A., Schmidt, P., and Waldman, D. M. (1980), "A Monte Carlo Study of Estimators of Stochastic Frontier Production Functions," *Journal of Econometrics* 13: 67–82.

Richmond, J. (1974), "Estimating the Efficiency of Production," *International Economic Review* 15(2): 515–521.

Schmidt, P. (1976), "On the Statistical Estimation of Parametric Frontier Production Functions," *Review of Economics and Statistics* 58: 238–239.

Schmidt, P. and Lin, T. F. (1984), "Simple Tests of Alternative Specifications in Stochastic Frontier Models," *Journal of Econometrics* 24: 349–361.

Thiry, B. (1985), *Une analyse de l'efficacité technique d'une société de transports intercommunaux Le cas de la STIL*, Travaux de recherches du CIRIEC, no. 85/07, Liege.

Van den Broeck, J., Forsund, F. R., Hjalmarsson, L., and Meeusen, W. (1980), "On the Estimation of Deterministic and Stochastic Frontier Production Functions. A Comparison," *Journal of Econometrics* 13: 117–138.

White, H. and MacDonald, G. L. (1980), "Some Large-Sample Tests for Nonnormality in the Linear Regression Model," *Journal of the Amercian Statistical Association* 75: 16–29.