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Variation in Productive Efficiency in French Workers' Cooperatives*

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Abstract

In this study, we explore the distribution of productive efficiency among workers' cooperatives operating in each of four sectors of French manufacturing. We use stochastic frontier panel data techniques to estimate production relationships in each sector, and to decompose output variation into input variation, variation in the effects of two indicators of the degree of worker participation in management, variation in productive efficiency, and an unexplained residual. In all four sectors we find that conventionally measured capital and labor inputs make a significant contribution to productivity. In only one sector do participation indicators contribute significantly. Variation in productive efficiency contributes significantly in all four sectors.

1. Introduction

The purpose of this study is to explore the distribution of productive efficiency among workers' cooperatives operating in each of four sectors of French manufacturing. Productive efficiency is one component of overall productivity, and although the measurement of productivity change (or variation) in European cooperatives has attracted much attention recently, for a variety of reasons the technical efficiency component of productivity change has been almost completely neglected. This study is an effort to remedy that neglect.

We have recent data on output, inputs, and other relevant variables for a number of workers' cooperatives operating in each of four sectors of French manufacturing for the two adjacent years 1987 and 1988. The sectors are architecture, printing, furniture, and public works. Thus we have four short two-year panels containing 24, 55, 22 and 42 firms, respectively.

We use recently developed stochastic frontier panel data techniques to estimate the production relationships within each sector. These techniques provide a decomposition of output variation into input variation, variation in a pair of variables representing the degree of participation of workers in management, variation in technical efficiency, and an unexplained residual.[1]

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The decomposition of productivity variation into input variation and participation variation is not new in this literature; see Jones and Svejnar [1985], Defourny, Estrin and Jones [1987], Defourny [1987] and Estrin, Jones and Svejnar [1987] for applications of this technique. The introduction of an additional component—efficiency variation—is new. Only Defourny [1988] and Sterner [1990] have sought to measure the technical efficiency of workers' cooperatives, in several sectors of the French economy and in the Mexican cement industry, respectively. However, Defourny estimated the mean technical efficiency, rather than individual efficiencies, over all cooperatives and over all capitalist firms in each sector. Consequently, he did not use efficiency variation to explain any part of intra-sectoral productivity variation.[2] Sterner compared technical efficiencies of individual plants with different ownership structures, but there were only two cooperatives in his sample.[3]

In all four sectors we find that conventionally measured capital and labor inputs make a significant contribution to productivity. In only two sectors do participation indicators contribute significantly. Variation in technical efficiency contributes significantly in all four sectors. One conclusion to be drawn from these findings is that it is risky to analyze productivity variation under the assumption of technical efficiency. To do so leads to an erroneous allocation of productivity variation to its other sources, which in turn can lead to inappropriate policy decisions, particularly those that may be designed to influence participation.

This article is organized as follows: in Section 2 we outline the production frontier model, its characteristics and its estimation; Section 3 contains a brief description of the data, and a discussion of the empirical results; and Section 4 concludes with a summary of the study and suggestions for further related research.

2. The Production Frontier Model

For a single cross section, Aigner, Lovell, and Schmidt [1977], Battese and Corra [1977] and Meeusen and van den Broeck [1977] all showed how to estimate a stochastic production frontier model of the form

$$\ln y_i = \alpha_0 + \sum_{j=1}^{K} \alpha_j \ln x_{ji} + v_i + u_i, \qquad i = 1, \ldots, I, \tag{1}$$

where y_i is observed output in the ith firm, x_{ji} is the observed amount of the jth input employed in the ith firm, $(\alpha_0, \alpha_1, \ldots, \alpha_K)$ is a vector of technology parameters to be estimated, $v_i \sim N(0, \sigma_v^2)$ is an error term capturing the random effects of noise, measurement error and the like, and u_i is a nonpositive error term, distributed independently of v_i, capturing the effects of technical inefficiency in production. Once a particular distribution is assigned to u_i—half normal, truncated normal, exponential and gamma have been used—its parameter(s) can be estimated and mean technical efficiency in the sample can be estimated. This is what Defourny [1988] did, using least squares methods.

Now we consider a time series of cross sections, and write the panel data extension of the cross section production frontier model (2.1) as

$$\ln y_{it} = \alpha_0 + \sum_{j=1}^{K} \alpha_j \ln x_{jit} + v_{it} + u_i, \qquad i = 1, \ldots, I,\ t = 1, \ldots, T_i, \tag{2}$$

where y_{it} is observed output of the ith firm in the tth period, and x_{jit} is observed usage of the jth input in the ith firm in the tth period. We have I firms and $T = \max\{T_i\}$ periods, although not all firms must be observed in all periods. Note that technical inefficiency is captured by the "firm effect," and is time-invariant. Models of this nature have been considered by several authors recently; this particular unbalanced panel version is adapted from Battese, Coelli, and Colby [1989].

In this study we use a standard Cobb-Douglas production function[4]

$$y_{it} = AK_{it}^{\alpha}L_{it}^{\beta}, \tag{3}$$

and incorporate the following institutional features of the cooperatives

$$K_{it} = K_{it}^{I} + K_{it}^{E} \tag{4}$$

and

$$L_{it} = L_{it}^{N} + L_{it}^{M}, \tag{5}$$

where K_{it}^{I} and K_{it}^{E} denote the amounts of fixed assets financed internally and externally, respectively, and where L_{it}^{N} and L_{it}^{M} denote the number of employees who are non-members and members of the cooperative, respectively, all in firm i in period t.[5] We now rewrite equation (3) as

$$y_{it} = AK_{it}^{\alpha}[(1 + (d - 1)(K_{it}^{E}/K_{it})]^{\alpha}\, L_{it}^{\beta}[(1 + (c - 1)(L_{it}^{N}/L_{it})]^{\beta}, \tag{6}$$

where d and c are parameters that allow for productivity differentials between K_{it}^{E} and K_{it}^{I}, and between L_{it}^{N} and L_{it}^{M}, respectively. In the event that $d = c = 1$, equation (6) collapses to equation (3), while if $d \neq 1$ or $c \neq 1$ there is a productivity differential between externally and internally financed fixed assets, or between nonmember and member employees. Following Brown and Medoff [1978], we take the logarithm of equation (6) and take linear approximations to the two bracketed terms to generate[6]

$$\ln y_{it} = \ln A + \alpha \ln K_{it} + \beta \ln L_{it} + \alpha(d - 1)(K_{it}^{E}/K_{it}) + \beta(c - 1)(L_{it}^{N}/L_{it}). \tag{7}$$

After reparameterization our stochastic production frontier model becomes

$$\ln y_{it} = a_0 + a_1 \ln K_{it} + a_2 \ln L_{it} + a_3(K_{it}^{E}/K_{it}) + a_4(L_{it}^{N}/L_{it}) + v_{it} + u_i. \tag{8}$$

The disturbance component v_{it} is assumed to be independently and identically distributed as $N(0, \sigma_v^2)$, independent of the disturbance component u_i, which is assumed to be independently and identically distributed as the nonpositive part of a $N(\mu, \sigma^2)$ distribution truncated above at zero. Both components are also assumed to be distributed independently of the exogenous variables in the model.

Firm-specific but time-invariant estimates of technical efficiency are obtained by following Jondrow et al. [1982] and Battese and Coelli [1988] to obtain

$$TE_i = E[\exp(u_i|v_{it} + u_i)] = \left\{\frac{1 - F(\sigma_i^* + (\mu_i^*/\sigma_i^*))}{1 - F(\mu_i^*/\sigma_i^*)}\right\} \exp(\mu_i^* + \tfrac{1}{2}\,\sigma_i^{*2}), \tag{9}$$

where F(·) is the cumulative distribution function of the standard normal variable and μ_i^* and σ_i^{*2} are the parameters of the conditional normal distribution of $(u_i|v_{it} + u_i)$. The mean technical efficiency of all firms in a sector is given by

$$TE = \left\{\frac{1 - F[\sigma + (\mu/\sigma)]}{1 - F(\mu/\sigma)}\right\} \exp(\mu + \tfrac{1}{2}\,\sigma^2). \tag{10}$$

Equation (8) is the model to be estimated, after which equations (9) and (10) are used to estimate time-invariant efficiency by observation and as a sample mean.

There are eight parameters to be estimated. The three technology parameters (a_0, a_1, a_2) describe the contribution of conventionally measured capital and labor inputs to output. The two participation parameters (d and c) measure the contribution of two popular indicators of participation to output. The three efficiency parameters [μ, $\tilde{\sigma}^2 = \sigma^2 + \sigma_v^2$ and $\gamma = \sigma^2/\tilde{\sigma}^2$] describe the contribution of technical efficiency to output. All eight parameters are estimated using maximum likelihood techniques described in Battese, Coelli, and Colby [1989] and Coelli [1989].

3. The data and the results

We use panel data covering 1987 and 1988 for cooperatives in four sectors: in Architecture we have 24 firms and 45 observations, in Printing, we have 55 firms and 110 observations, in Furniture we have 22 firms and 41 observations, and in Public Works we have 42 firms and 81 observations. Output y_{it} is value added in thousand FF, capital K_{it} is the value of fixed assets in thousand FF, labor L_{it} is the number of employees, and K_{it}^E/K_{it} and L_{it}^N/L_{it} are ratios of external capital to total capital and non-member workers to total workers, respectively. The data were obtained from CGSCOP [1989], and are summarized in table 1.

Having only two years of data, we think the fixed effects model gives reliable estimates of technical efficiency. We use maximum likelihood methods to obtain estimates of a_0, a_1, a_2, a_3, a_4, μ, $\tilde{\sigma}^2$ and γ and their standard errors.[8] The participation parameters c and d are also identified, and so we estimate them and their standard errors as well.[9] The results for each of the four sectors are presented in tables 2–5. Each table reports the results of four model specifications, in which different restrictions are imposed on the parameters. Student t-statistics are reported beneath parameter estimates. The χ^2 statistic provides a test of the hypothesis that variation in technical efficiency contributes nothing to productivity variation; the hypothesis is that $\gamma = 0$.

Table 1. Data.

	y (Thousand FF)	K (Thousand FF)	L (Number of Employees)	K^E/K	L^N/L
Furniture					
Mean	4373.92	3128.02	28	0.13	0.26
Min	96.12	144.18	3	0.0	0.0
Max	93133.51	83150.54	409	0.46	0.70
Printing					
Mean	3659.63	2941.38	20	0.12	0.23
Min	61.00	80.64	2	0.0	0.0
Max	20206.99	21105.36	88	0.75	0.69
Public Works					
Mean	8276.71	4189.22	44	0.16	0.43
Min	390.94	26.80	2	0.0	0.0
Max	66123.66	44846.77	343	0.99	0.90
Architecture					
Mean	1100.46	227.51	5	0.10	0.15
Min	253.23	8.96	2	0.0	0.0
Max	3217.74	1037.63	18	0.43	0.55

As mentioned in the introduction, we seek to quantify the contributions of three sources of productivity variation. Although there are clear differences across the four sectors, we provide a functional summary of the results by focusing on the contributions of inputs, participation and efficiency to output in the four sectors.

The role of inputs: Estimated output–capital elasticities are stable across models, with values in the (0.1, 0.2) range, and are frequently significantly greater than zero. Estimated output–labor elasticities are also stable across models, with values in the (0.9–1.0) range, and are always significantly greater than zero. Consequently, scale economies appear to play a role in all four sectors, with estimated scale elasticities falling in the (1.0–1.2) range, although they are only occasionally significantly greater than unity.

The role of participation: One way of measuring the impact of participation is to examine the estimated coefficients on the two participation variables. These estimated coefficients are not significantly different from zero in two sectors (Architecture and Public Works); they are suggestively close to being significantly different from zero in the Furniture sector; and they are clearly significantly different from zero in the Printing sector. Where significant, these estimated coefficients are negative, suggesting that increased participation leads to increases in output. A second way of measuring the impact of participation on output is through use of likelihood ratio tests, which we leave to the reader. These tests tell much the same story. A third way of measuring the impact of participation is to derive estimates of $(d - 1)$ and $(c - 1)$ from the coefficient estimates, and then to calculate approximate standard errors of the estimated values of $(d - 1)$ and $(c - 1)$, respectively. Results of these calculations are consistent with the first two sets of tests, and suggest that participation indicators exert a significantly positive impact on output in the Printing sector, and they come close to doing so in the Furniture sector. They do not have a significant

Table 2. Panel frontier results for architecture cooperatives. Dependent Variable: ln y_{it}

Independent Variable	Coefficient	MLE Parameter Estimates Model 1	2	3	4
Constant	a_0	4.2310 (12.5588)	4.1966 (12.6411)	4.2294 (12.6588)	4.1955 (12.5725)
ln K_{it}	a_1	0.2144 (4.1791)	0.2060 (4.3046)	0.2143 (4.1762)	0.2060 (4.3086)
ln L_{it}	a_2	1.0215 (5.7717)	1.0544 (6.5458)	1.0242 (6.2137)	1.0566 (7.0454)
$(K^E/K)_{it}$	a_3	−0.1881 (−0.4508)	—	−0.1879 (−0.4502)	—
$(L^N/L)_{it}$	a_4	0.0128 (0.0431)	0.0108 (0.0363)	—	—
	$\tilde{\sigma}^2$	0.1212 (2.4415)	0.1210 (2.4440)	0.1214 (2.4577)	0.1212 (2.4755)
	γ	0.2288 (0.5281)	0.2210 (0.5022)	0.2306 (0.5379)	0.2230 (0.5134)
	μ	0	0	0	0
	ln £	−12.7418	−12.8439	−12.7427	−12.8445
	$\chi^2_{(1)}$	5.5029	4.3492	4.3960	3.2799
	RTS	1.2359 (1.4908)	1.2604 (1.7528)	1.2385 (1.6411)	1.2626 (1.9150)
	d − 1	−0.8773 (−0.6235)	—	−0.8768 (−0.4495)	—
	c − 1	0.0125 (0.0313)	0.0102 (0.0361)	—	—
Mean Efficiencies by Cooperative					
Firm	NOBS				
1	2	0.8930	0.8898	0.8926	0.8893
2	2	0.8910	0.8933	0.8904	0.8927
3	2	0.9105	0.9107	0.9101	0.9103
4	2	0.8902	0.8923	0.8900	0.8920
5	2	0.9017	0.9050	0.9013	0.9047
6	2	0.9283	0.9273	0.9280	0.9269
7	2	0.7928	0.7875	0.7913	0.7859
8	2	0.8818	0.8875	0.8816	0.8871
9	2	0.9032	0.8981	0.9032	0.8980
10	2	0.9048	0.9065	0.9044	0.9060
11	1	0.9008	0.9031	0.9003	0.9026
12	2	0.8884	0.8931	0.8880	0.8926
13	2	0.8825	0.8821	0.8822	0.8818

Table 2. continued

Mean Efficiencies by Cooperative		MLE Parameter Estimates			
		Model			
Firm	NOBS	1	2	3	4
14	2	0.8674	0.8731	0.8675	0.8731
15	1	0.8775	0.8808	0.8767	0.8800
16	2	0.8653	0.8682	0.8644	0.8673
17	2	0.8421	0.8498	0.8417	0.8493
18	2	0.8607	0.8664	0.8603	0.8659
19	2	0.8842	0.8848	0.8836	0.8841
20	2	0.8011	0.8062	0.7995	0.8045
21	2	0.8537	0.8612	0.8527	0.8602
22	2	0.8326	0.8380	0.8322	0.8375
23	2	0.9233	0.9230	0.9233	0.9229
24	1	0.9353	0.9357	0.9353	0.9357
Overall Mean Score		0.8798	0.8818	0.8793	0.8813

effect in the two remaining sectors. Our finding of a significant positive effect of participation in the Printing sector is consistent with results of Defourny, Estrin, and Jones [1987]. Among the six sectors in which they studied the performance of cooperatives, Printing also emerged as a sector in which the productivity enhancing effect of workers' participation was particularly important. This common finding may be linked to the fact that the cooperative movement has long been very active in Printing, with its skilled workers, strong personal involvement, and militancy.

The role of efficiency: Efficiency plays a substantial, and statistically significant, role in all four sectors. Estimated values of γ, the ratio of the variance of the efficiency element in the composed error term to the variance of the composed error term itself, are statistically significant in the majority of models. More to the point, the chi-square statistics, which test the improvement in explanatory power of MLE over OLS, suggest that the parameters of the one-sided component of the composed error structure are statistically significant in all cases. In all sectors the impact of inefficiency is captured by two parameters, σ^2 and γ; in no sector did the model converge with a statistically significant value of μ.

The time-invariant estimates of technical efficiency for each cooperative enterprise in each sector are reported in the lower half of tables 2–5. These efficiencies show little variation across models, suggesting that the specification is robust to variation in the participation component of the model. The efficiencies vary substantially across sectors, with sample means declining from 0.88 in Architecture to 0.80 in Printing, 0.77 in Public Works, and 0.74 in Furniture. The efficiencies also vary substantially within each sector, with scores in Model 1 ranging from 0.79 to 0.93 in Architecture, from 0.59 to 0.93 in Printing, from 0.45 to 0.94 in Furniture, and from 0.45 to 0.96 in Public Works. This variation in productive efficiency goes a long way toward explaining observed variation in output within each sector.

Table 3. Panel frontier results for printing cooperatives. Dependent Variable: $\ln y_{it}$

Independent Variable	Coefficient	MLE Parameter Estimates: Model 1	Model 2	Model 3	Model 4
Constant	a_0	4.8581	4.8552	4.6858	4.5776
		(21.7339)	(21.8062)	(21.0673)	(19.9383)
$\ln K_{it}$	a_1	0.0802	0.0693	0.1196	0.1331
		(2.2724)	(1.9017)	(3.5449)	(3.8013)
$\ln L_{it}$	a_2	1.0253	1.0446	0.9504	0.9373
		(15.3438)	(15.1135)	(16.8060)	(15.7294)
$(K^E/K)_{it}$	a_3	−0.4920	—	−0.6823	—
		(−1.8197)		(−2.6805)	
$(L^N/L)_{it}$	a_4	−0.5284	−0.6613	—	—
		(−2.6885)	(−3.4813)		
	$\tilde{\sigma}^2$	0.2151	0.2188	0.2319	0.2686
		(3.5142)	(3.5430)	(3.8753)	(3.6509)
	γ	0.4016	0.3800	0.4329	0.5021
		(2.0924)	(1.8650)	(2.5470)	(3.0339)
	μ	0	0	0	0
	ln £	−53.7778	−55.9284	−56.2136	−59.9991
	$\chi^2_{(1)}$	7.4121	6.6459	7.1295	7.9143
	RTS	1.1055	1.1139	1.0700	1.0704
		(1.8178)	(1.9213)	(1.3142)	(1.2023)
	$d - 1$	−6.1347	—	−5.7048	—
		(−1.5102)		(−2.0517)	
	$c - 1$	−0.5154	−0.6331	—	—
		(−1.2105)	(−8.4719)		
Mean Efficiencies by Cooperative					
Firm	NOBS				
1	2	0.7972	0.8115	0.7824	0.7694
2	2	0.8336	0.8260	0.8398	0.8093
3	2	0.8061	0.8225	0.7891	0.7839
4	2	0.7971	0.8082	0.7923	0.7853
5	2	0.7874	0.8031	0.7829	0.7810
6	2	0.8926	0.8881	0.8925	0.8771
7	2	0.8768	0.8813	0.8739	0.8705
8	2	0.7469	0.7629	0.7442	0.7328
9	2	0.8096	0.8106	0.7873	0.7520
10	2	0.6837	0.6736	0.6804	0.6131
11	2	0.5921	0.6174	0.5670	0.5432
12	2	0.8388	0.8394	0.8111	0.7772
13	2	0.8941	0.8954	0.8849	0.8761

Table 3. continued

Mean Efficiencies by Cooperative		MLE Parameter Estimates			
		Model			
Firm	NOBS	1	2	3	4
14	2	0.8053	0.8222	0.7690	0.7578
15	2	0.7370	0.7250	0.7546	0.7033
16	2	0.8049	0.8182	0.7994	0.7971
17	2	0.8289	0.8287	0.8324	0.8115
18	2	0.7786	0.7925	0.7690	0.7554
19	2	0.8907	0.8159	0.8222	0.8191
20	2	0.7393	0.7541	0.7365	0.7190
21	2	0.8710	0.8577	0.8407	0.7770
22	2	0.7443	0.7185	0.7593	0.6787
23	2	0.7122	0.7219	0.7287	0.7111
24	2	0.8503	0.8544	0.8492	0.8396
25	2	0.7336	0.7566	0.7155	0.7134
26	2	0.8782	0.8311	0.8832	0.7912
27	2	0.8504	0.8567	0.8575	0.8563
28	2	0.8534	0.8713	0.7891	0.7862
29	2	0.7436	0.7688	0.7095	0.7025
30	2	0.6572	0.6967	0.5904	0.5719
31	2	0.8565	0.8301	0.8578	0.7966
32	2	0.8356	0.8475	0.8147	0.8079
33	2	0.7985	0.7690	0.8233	0.7666
34	2	0.9286	0.9330	0.9080	0.9091
35	2	0.9290	0.9261	0.9295	0.9276
36	2	0.8071	0.8184	0.8117	0.8120
37	2	0.8825	0.8891	0.8538	0.8455
38	2	0.7539	0.7717	0.7292	0.7200
39	2	0.8467	0.8566	0.8386	0.8399
40	2	0.8467	0.8534	0.8531	0.8542
41	2	0.7825	0.7892	0.7441	0.7074
42	2	0.6584	0.6454	0.5786	0.4752
43	2	0.8559	0.8229	0.8713	0.8112
44	2	0.8426	0.8496	0.8460	0.8414
45	2	0.9256	0.9260	0.9274	0.9278
46	2	0.7928	0.8043	0.8023	0.8033
47	2	0.7444	0.7556	0.7673	0.7625
48	2	0.8367	0.8509	0.8118	0.8133
49	2	0.8113	0.8248	0.8048	0.8027
50	2	0.7278	0.6855	0.6937	0.5591
51	2	0.7418	0.7638	0.6928	0.6776
52	2	0.8895	0.8951	0.8731	0.8706
53	2	0.8358	0.7778	0.7960	0.6113
54	2	0.6595	0.6907	0.6251	0.6126
55	2	0.7516	0.7110	0.7216	0.5923
Overall Mean Score		0.8028	0.8059	0.7901	0.7632

Table 4. Panel frontier results for furniture cooperatives. Dependent Variable: ln y_{it}

Independent Variable	Coefficient	MLE Parameter Estimates — Model 1	2	3	4
Constant	a_0	3.7444 (4.0135)	4.1210 (4.2149)	3.5304 (5.3755)	3.9651 (6.7151)
ln K_{it}	a_1	0.2759 (1.2024)	0.1726 (0.4705)	0.2795 (2.1170)	0.1411 (1.2536)
ln L_{it}	a_2	0.8866 (3.5658)	0.9717 (1.2200)	0.8840 (8.9588)	1.0293 (10.9101)
$(K^E/K)_{it}$	a_3	−0.8206 (−0.8183)	—	−0.9007 (−1.5425)	—
$(L^N/L)_{it}$	a_4	−0.6856 (−2.2005)	−0.7385 (−1.9891)	—	—
	$\tilde{\sigma}^2$	0.1920 (2.7934)	0.2219 (0.6404)	0.1826 (1.2874)	0.2308 (1.4005)
	γ	0.8353 (8.0606)	0.8719 (3.2549)	0.7262 (2.5192)	0.7700 (3.4276)
	μ	0	0	0	0
	ln £	−3.7674	−4.0023	−7.4889	−8.7876
	$\chi^2_{(1)}$	13.2057	16.6850	8.6422	9.3057
	RTS	1.1625 (2.6144)	1.1443 (0.3041)	1.1635 (1.7275)	1.1704 (1.9329)
	d − 1	−2.9743 (−0.9180)	—	−3.2225 (−1.7608)	—
	c − 1	−0.7733 (−0.6660)	−0.7600 (−1.8176)	—	—
Mean Efficiencies by Cooperative					
Firm	NOBS				
1	2	0.7713	0.6654	0.8498	0.7782
2	2	0.8799	0.8910	0.7445	0.7193
3	2	0.6407	0.5520	0.7674	0.6640
4	2	0.7467	0.7359	0.8220	0.8077
5	1	0.7638	0.7265	0.8151	0.7622
6	2	0.9477	0.9294	0.9213	0.8837
7	2	0.7522	0.6462	0.7935	0.6839
8	2	0.9046	0.9099	0.9165	0.9139
9	2	0.6628	0.7382	0.7289	0.7850
10	2	0.6301	0.5965	0.6277	0.5792
11	1	0.8902	0.8986	0.8989	0.8897
12	2	0.8536	0.8973	0.8533	0.8725
13	2	0.9025	0.8785	0.9034	0.8719

Table 4. continued

Mean Efficiencies by Cooperative		MLE Parameter Estimates			
		Model			
Firm	NOBS	1	2	3	4
14	2	0.5893	0.6092	0.6803	0.7064
15	2	0.8219	0.8440	0.8927	0.9056
16	2	0.4884	0.4256	0.5799	0.4832
17	2	0.8859	0.8861	0.7992	0.7664
18	2	0.8473	0.8879	0.7846	0.8187
19	2	0.6662	0.7279	0.6213	0.6595
20	2	0.5275	0.4745	0.5131	0.4721
21	1	0.4531	0.4089	0.5547	0.5117
22	1	0.6477	0.6987	0.7083	0.7607
Overall Mean Score		0.7422	0.7271	0.7648	0.7359

Overall impressions: Output variation across cooperative enterprises is significantly related to input variation across enterprises in all four sectors. But that is only part of the story. Output variation is also significantly and positively affected by increases in participation in one sector. Output variation is also significantly affected by variation in productive efficiency in all four sectors. The conclusion is that any model that attempts to explain productivity performance exclusively in terms of conventionally measured inputs is bound to generate misleading results concerning the absolute and relative importance of those inputs. It is sometimes necessary to examine the extent to which members of the cooperative finance or supply these inputs, and it is always necessary to examine the efficiency with which management coordinates the employment of these variables.

4. Summary and suggestions

In this article we have employed stochastic frontier panel data techniques to investigate the magnitude and distribution of productive efficiency in samples of producer cooperatives operating in four sectors of French industry. The economic finding of primary interest concerns the role of efficiency variation in explaining observed output variation. That role is statistically significant in all four sectors. In addition, the role of two popular indicators of worker participation is significantly positive in one sector. This suggests that conclusions about productivity variation, and policy recommendations emanating therefrom, based on econometric analysis with symmetric error structures and without participation variables, may be very misleading.

It would be of interest to reanalyze the same data using nonparametric, nonstochastic techniques to compare the performance of the two approaches. The nonparametric construction and decomposition of the Malmquist index into productivity variation and efficiency variation recently developed by Färe et al. [1989] would provide an ideal counterpart to our stochastic parametric approach.

Table 5. Panel frontier results for public works cooperatives. Dependent Variable: ln y_{it}

Independent Variable	Coefficient	MLE Parameter Estimates: Model 1	2	3	4
Constant	a_0	4.1330 (4.8408)	4.5860 (4.7209)	4.2925 (22.3826)	4.5013 (26.1761)
ln K_{it}	a_1	0.2009 (1.8209)	0.1634 (1.3118)	0.1665 (5.1396)	0.1435 (4.4837)
ln L_{it}	a_2	0.8595 (11.5334)	0.8689 (15.0722)	0.9514 (12.2352)	0.9636 (24.0603)
$(K^E/K)_{it}$	a_3	0.3656 (1.1580)	—	0.2960 (1.2083)	—
$(L^N/L)_{it}$	a_4	0.3683 (0.8930)	0.2730 (1.0726)	—	—
	$\tilde{\sigma}^2$	0.1475 (7.2110)	0.2247 (4.6128)	0.1781 (2.6249)	0.1917 (2.7814)
	γ	0.8262 (13.9386)	0.8886 (20.3922)	0.8100 (8.3282)	0.8300 (9.4723)
	μ	0	0	0	0
	ln £	−4.1414	−5.7854	−6.0338	−8.2930
	$\chi^2_{(1)}$	16.4122	22.7723	16.9051	16.7397
	RTS	1.0604 (1.0307)	1.0323 (0.2843)	1.1179 (1.9815)	1.1071 (3.5581)
	d − 1	1.8198 (2.1567)	—	1.7778 (1.0974)	—
	c − 1	0.4285 (0.8399)	0.4058 (1.3410)	—	—
Mean Efficiencies by Cooperative					
Firm	NOBS				
1	2	0.7481	0.7252	0.7416	0.7407
2	2	0.6879	0.5891	0.7270	0.6745
3	2	0.6448	0.6227	0.7046	0.6337
4	2	0.7258	0.6664	0.6859	0.6740
5	2	0.6488	0.6043	0.6437	0.6232
6	2	0.6633	0.5881	0.6361	0.6555
7	2	0.6966	0.6601	0.6473	0.6260
8	2	0.6167	0.5479	0.6139	0.5743
9	2	0.9102	0.8964	0.9171	0.9232
10	2	0.7739	0.7162	0.7050	0.6810
11	2	0.6608	0.5664	0.5917	0.5642
12	2	0.7200	0.6300	0.6797	0.6551
13	2	0.9299	0.3515	0.8765	0.9291

Table 5. continued

Mean Efficiencies by Cooperative		MLE Parameter Estimates			
		Model			
Firm	NOBS	1	2	3	4
14	2	0.7997	0.6726	0.7550	0.7092
15	2	0.7666	0.7883	0.8245	0.8547
16	2	0.9615	0.9532	0.9620	0.9602
17	2	0.8797	0.9560	0.3672	0.8525
18	2	0.8647	0.7737	0.8157	0.7864
19	2	0.7921	0.6647	0.7450	0.6879
20	2	0.8713	0.7365	0.7927	0.7446
21	2	0.8543	0.9261	0.8262	0.9006
22	2	0.7733	0.6746	0.7613	0.7210
23	2	0.8974	0.9293	0.8921	0.9411
24	2	0.6994	0.6271	0.6240	0.6126
25	2	0.6925	0.5804	0.6719	0.6239
26	2	0.9484	0.9092	0.8991	0.8758
27	2	0.8680	0.7605	0.8020	0.7528
28	2	0.7746	0.6493	0.7581	0.7051
29	2	0.4529	0.3944	0.4856	0.4689
30	2	0.9290	0.8730	0.8767	0.8510
31	1	0.8830	0.8365	0.8794	0.8608
32	2	0.5077	0.4479	0.4879	0.4777
33	2	0.5691	0.5480	0.6036	0.6292
34	2	0.8852	0.7765	0.8211	0.7724
35	2	0.8984	0.8049	0.7920	0.7543
36	2	0.6442	0.5377	0.6434	0.5861
37	2	0.9271	0.7857	0.9095	0.8442
38	2	0.8640	0.7504	0.7938	0.7507
39	1	0.7011	0.5484	0.7089	0.6295
40	2	0.5049	0.4844	0.5395	0.5592
41	2	0.6545	0.5281	0.6810	0.6220
42	1	0.4631	0.4126	0.5028	0.4972
Overall Mean Score		0.7727	0.7238	0.7567	0.7471

Notes

1. Our model is parametric, and so the decomposition we obtain is conditional on both the functional form of the production function we estimate (Cobb–Douglas) and the functional form of the error component intended to capture productive inefficiency (half-normal).
2. However, by segmenting his sample into size classes, Defourny was able to test hypotheses concerning variation of technical efficiency over size classes.
3. One can also mention Côté [1989], who measured technical efficiency in private, public and cooperative U.S. electric utilities, but his sample included only consumer cooperatives, and he estimated only mean technical efficiencies.
4. The Cobb–Douglas functional form is used in this study because single equation translog rarely works, and did not work with these data.

5. Since internal and external capital resources are used together to finance most types of asset purchases, it is impossible to know precisely what proportion of fixed assets is internally financed. We took the percentage of equity capital held by workers (as opposed to the percentage held by nonworkers) as an approximation to this proportion.
6. This approximation has been applied before in this literature, by Jones and Svejnar [1985] and Defourny [1987], but only for the labor input. The approximations are obtained by taking Taylor series expansions of the two nonlinear participation terms in equation (6) around the points $d = 1$ and $c = 1$ respectively, and truncating each expansion at the first-order term. Lovell, Sickles, and Warren [1988] have shown that if $c = d = 1$ the linear approximations are exact, and equation (7) correctly shows that participation has no effect on productivity. However if $c \neq 1$ or $d \neq 1$, then although equation (7) correctly identifies the directions of the participation effects, it overstates their magnitudes, and the approximation errors increase in magnitude as c or d depart from unity. Of course it would be possible to embed the nonlinear model (6) directly into a stochastic frontier panel data framework and avoid the approximation error issue altogether. We have not done so. Consequently, we interpret our empirical findings as establishing upper bounds on the likely impacts of participation on productivity in these sectors.
7. Initially we tried a two-stage formulation. In the first stage, we estimated a stochastic Cobb-Douglas production frontier (2). In the second stage, we attempted to use the two participation variables to explain variation in measured efficiency by performing regressions of the general form

$$\hat{u}_i = f(E(K_{it}^E/K_{it}), E(L_{it}^N/L_{it})),$$

where the expectation is taken over time. When we found no significant correlation between $\hat{u}_i$ and the means of the two participation indicators, we turned to the single stage formulation (8). In this formulation participation influences productivity not by influencing efficiency, but by altering production possibilities.
8. We use a computer program written by Coelli [1989].
9. $(d - 1) = a_3/a_1 = f(a_1, a_3)$ and $(c - 1) = a_4/a_2 = g(a_2, a_4)$. The functions f and g are nonlinear, and so we use linear approximations to obtain estimated standard errors of the estimated values of d and c. If we have $\hat{b} = h(\hat{a})$, where $\hat{a}$ is a vector and $\hat{b}$ is a scalar and if ∇h is the gradient vector and Σ is the variance-covariance matrix, then by approximation we have

$$h(\hat{a}) - h(a) \approx [\nabla h(a)]^T(\hat{a} - a),$$

and the variance of $\hat{b}$ is given by

$$\mathrm{var}(\hat{b}) = [\nabla h(a)]^T\, \Sigma[V\nabla h(a)].$$

See also N'Gbo [1991].

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