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DIPARTIMENTO DI ECONOMIA POLITICA

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Technology and Efficiency in a Panel of Italian Dairy Farms: A SGM Restricted Cost Function Approach

n.258 - Luglio 1999

TECHNOLOGY AND EFFICIENCY IN A PANEL OF ITALIAN DAIRY FARMS: A SGM RESTRICTED COST FUNCTION APPROACH.

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Summary

The paper contributes to the literature on flexible functional forms by proposing a short term specification of the SGM cost function. The original version of Diewert and Wales (1987) is modified to allow for quasi-fixed factors of production and variable returns so that the effects of sub-equilibrium and scale economies can be adequately investigated. The resulting SGM restricted cost function is flexible, parsimonious and (globally) curvature correct. A balanced panel of 41 Italian dairy farms during the years 1980 to 1992 serves as case study. A two-step procedure is used to estimate first the technology parameters and then farm level efficiency. No distributional assumptions are required in the second stage to separate input technical efficiency out of the residual component as we consider a fixed effects model; farm level effects can vary according to a pre-specified second degree polynomial of time. Empirical results indicate that input demands are inelastic, there exist economies of scale and a substantial excess of capacity; technical change is biased in favor of purchased feeds and hired labor, while the panel technical efficiency is rather low.

[♥] We thank Marco Tucci for valuable suggestions.

1. Introduction

The objective of the paper is to develop and estimate a model for analyzing the production relationships between aggregate output and variable inputs as well as input technical efficiency. The short-term technology is depicted from the dual and consists of one aggregate output, three variable inputs (purchased feed, other intermediate consumption, hired labor), two quasi-fixed inputs (self-employed labor and capital). As case study we use a balanced panel of 41 specialized dairy farms located in the plain of Po river in Italy. The investigation period covers the years from 1980 to 1992.

The original contribution of the paper is that it modifies the symmetric generalized McFadden (SGM) cost function (Diewert and Wales, 1987) by including quasi-fixed inputs as arguments. The proposed version is flexible, parsimonious and (globally) curvature correct. This modest extension allows short run behavior to be taken into account while maintaining the consistency of the estimated restricted cost function with microeconomic theory and approximation properties.

There is a relatively large theoretical and applied literature on the SGM cost function. Kumbhakar (1990), in his study on U.S. airlines, generalizes it by including network and control variables. Kumbhakar (1994) introduces a multi-product version that permits zero values of one or more of the outputs. However, as far as we know, this is the only example of SGM restricted cost function besides that of Rask (1995). In his work a modified SGM cost function for Brazilian sugarcane production is estimated and the presence of technical change and economies of scale is investigated. His formulation, however, is too restrictive since it can not accommodate the full range of implications. In fact, only first-order relationships of quasi-fixed inputs do appear, and not all of them. This is a limitation in a few respects: first, shadow values depend only on output level, consequently the temporary equilibrium model is not consistent with the steady-state solution of quasi-fixed inputs; second, in empirical applications there is no guarantee that the appropriate convexity conditions will be (locally or globally) satisfied, however, one does not have any criterion for evaluating them; third, as the resulting cost function is not quadratic in all its arguments unnecessary restrictions are placed on the estimated technology. In our study we hope to overcome those problems as well as give a piece of evidence on the structure of the dairy farms in the panel.

The remainder of this paper is organized as follows. Section 2 focuses on the analytical framework adopted to investigate the farming activity of the dairy sector. Section 3 contains a brief discussion of our balanced panel and variable construction. In section 4, a two-step procedure is used to estimate first the parameters of variable input demands and then farm level efficiency. Production relationships are analyzed through a set of elasticities of both variable inputs and shadow prices. Given the short-term framework of analysis cost flexibility is decomposed into scale economies and overall capacity utilization. Variable cost elasticities with respect to quasi-fixed inputs, the utilization index, and scale economies, are presented at farm level. The effect of technological bias on input use is also examined. In the second stage, no distributional assumptions are required to separate input technical efficiency out of the residual component as we consider a fixed effects model, which is a common working assumption when panel data are available. Since the investigation period is relatively long individual effects are allowed to vary according to a pre-specified second degree polynomial of time. Section 5 presents some concluding comments.

2. Analytical framework

In this study we maintain that the objective of farmers is to minimize the cost of producing a given level of output, conditional on input prices, stocks of quasi-fixed inputs and (a proxy of) exogenous technical change. Under some regularity conditions, duality principles ensure consistency between variable cost and production functions, so that either one will describe the farming activity equally well (Chambers, 1988). The general form of the restricted cost model is the following:

(1) $$VC = G^{*}(Y, W, Z, t)$$

where VC is variable cost, Y is output, $W \equiv (W_1, W_2, ..., W_N)'$ is the vector of input prices, $Z \equiv (Z_1, Z_2, ..., Z_M)'$ is the vector of fixed inputs, and t is the time trend. The function G^* will satisfy the following properties: linearly homogeneous, non-decreasing and concave in W, non-decreasing in Y, non-increasing and convex in Z, non-negative, continuos and twice continuously differentiable in all its arguments.

Empirically, the nature of the cost function (1) is unknown. A number of current studies approximate it by means of translog or quadratic restricted cost functions. We use the SGM form because it is flexible, in the sense of providing a second-order approximation to an unknown function at any given point (Diewert, 1976); it has a hessian of constants, thus the curvature properties hold globally so that can be tested and, possibly, imposed without destroying flexibility (Diewert and Wales, 1987, p. 54); finally, it is invariant to normalization.

In this study, we depart from Diewert and Wales formulation by adding quasi-fixed inputs.

2.1 The SGM restricted cost function

Consider the following SGM variable cost function[1] with long run variable returns to scale (VRTS) to approximate the unknown $G^*(.)$:

(2)
$$G(.) = g(W)Y + \sum_i b_{ii} W_i Y + \sum_i b_i W_i + \sum_i b_{it} W_i tY + b_t(\alpha' W)t + b_{YY}(\beta' W)Y^2 + b_{tt}(\gamma' W)t^2 Y + \sum_i \sum_k d_{ik} W_i Z_k + \sum_k c_{kY}(\delta' W) Z_k Y + \sum_k c_{kt}(\lambda' W) Z_k t + .5 \sum_j \sum_k c_{jk}(\eta' W)\frac{Z_j Z_k}{Y}$$

where g(W) is defined by:

(3)
$$g(W) = \frac{W' SW}{2\theta' W} = \frac{\sum_i \sum_h s_{ih} W_i W_h}{2\sum_i \theta_i W_i}$$

where S is a NxN symmetric negative semidefinite (nsd) matrix such that $S'W^*=0$ with $W^*>>0$, and i, h denote variable inputs, and j, k fixed inputs. Since W^* is chosen to be the vector of ones, we have $\sum_h s_{ih}=0$ for all i, and the rank of S is (N-1). $\theta=(\theta_1,...,\theta_N)'$ is a vector of non-negative constants not all zero and $c_{jk}=c_{kj}$.

It can be shown that G(.) is a flexible (linearly homogeneous in W) restricted cost function at any point (Y^*,W^*,Z^*,t^*) provided that $W^*>>0$, $\theta' W^*\neq 0$, $\alpha' W^*\neq 0$, $\beta' W^*\neq 0$, $\gamma' W^*\neq 0$, $\delta' W^*\neq 0$, $\lambda' W^*\neq 0$, $\eta' W^*\neq 0$. On the other hand, G(.) is globally concave in W if $S=\{s_{ih}\}$ is negative semidefinite and globally convex in Z if $C=\{c_{jk}\}$ is positive semidefinite. We want the functional form to be parsimonious, too; i.e., that it can provide the second-order approximation using a minimal number of parameters (Diewert and Wales, 1995). So, the parameter vector θ, along with α, β, γ, δ, λ, η are assumed to be exogenously given[2]. Thus, there are (N+M)(N+M+1)/2 + 2(N+M) + 3 free parameters to be estimated - just enough for the SGM variable cost function to be flexible at the point (Y^*,W^*,Z^*,t^*).

If the estimated S matrix does not conform to concavity criteria, negative semidefiniteness can be imposed at each data point[3] by reparameterizing it as S=-TT', where T is

1 In terms of (2), if $d_{ik}=c_{kt}=c_{jk}=0$, for each i, j, k and t, we get back Rask's version (1995).
2 The inner products can be thought of as fixed-weight price indexes. We will assume that they have the Laspeyres form with fixed weights given by the mean quantities (Diewert and Wales, 1987; Kohli, 1993). Further, we assume that $\theta = \alpha = \beta = \gamma = \delta = \lambda = \eta$. In this case, $\theta' W^* = 1$ and $\theta > 0$, and similarly for the remaining fixed weight vectors. See Appendix A for a proof of flexibility.
3 The imposition of required curvature does not destroy flexibility. Though, by reducing the rank of the reparameterized hessian we reduce the range of second order effects and move to a semiflexible version (Diewert and Wales, 1988; Moschini, 1998; Ryan and Wales, 1996). Empirically, it does happen that the rank reduction is equal to the number of the hessian eigenvalues with wrong signs.

a lower triangular matrix. Global convexity in quasi-fixed inputs Z can be stated (imposed) analogously upon the positive semidefiniteness of the estimated matrix C.

For econometric implementation, a consistent set of cost-minimizing variable input demands can be derived based on Shephard's lemma. Here, optimal input-output coefficients ($X_i/Y = (\partial G/\partial W_i)/Y$) are considered to reduce possible heteroskedasticity:

(4)
$$\frac{X_i}{Y} = \left\{ \frac{S^{(i)}W}{\theta' W} - \frac{\theta_i}{2}\frac{W' SW}{\left(\theta' W\right)^2} \right\} + b_{ii} + \frac{b_i}{Y} + b_{it}t + \frac{\alpha_i b_t t}{Y} + \beta_i b_{YY} Y + \gamma_i b_{tt} t^2 + \sum_k d_{ik}\frac{Z_k}{Y} +$$
$$\delta_i \sum_k c_{ky} Z_k + \lambda_i \sum_k c_{kt}\frac{Z_k t}{Y} + \frac{\eta_i}{2}\sum_j \sum_k c_{jk}\frac{Z_j Z_k}{Y^2}$$

Note that the system (4) contains all parameters of the SGM restricted cost function. Thus, in principle, we needn't provide an enlarged set of equations[4].

2.2 Demand and cost elasticities

As the estimated parameters are not directly interpretable, we base our analysis on price and cost elasticities[5]. Substitution possibilities among factors of production are examined using short run price elasticities, $\varepsilon_{ih}=\partial \ln X_i/\partial \ln W_h$, with $\Sigma_h \varepsilon_{ih}=0$, $\forall i$, which are proportional to Allen-Uzawa elasticities of substitution, defined as $\sigma_{ih}=\varepsilon_{ih}/\omega_h$, where $\omega_h=X_h W_h/G$ is the cost share. Concerning scale elasticities we have $\varepsilon_{iY}=\partial \ln X_i/\partial \ln Y$ which tells something about input normality and $\varepsilon_{ik}=\partial \ln X_i/\partial \ln Z_k$, respectively. The shadow price responses with respect to variable input prices are defined analogously, $\varphi_{kh}=\partial \ln F_k/\partial \ln W_h$, with $\Sigma_h \varphi_{kh}=1$, $\forall k$. These parameters are interpretable as indirect measures of utilization; $\varphi_{kh}>0$, e.g., means that a rise in W_h brings about a positive change in F_k. Looking at shadow price as marginal reward of desired stock, its

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[4] However, greater efficiency in estimation can be gained by forcing more structure on the data without reducing degrees of freedom, e.g., including additional information in the form of shadow value equations. Such equations take the form:

(5)
$$-F_k = \sum_i d_{ik} W_i + c_{ky}\left(\delta' W\right)Y + c_{kt}\left(\lambda' W\right)t + \sum_j c_{jk}\left(\eta' W\right)\frac{Z_j}{Y}$$

This expression represents the potential reduction in variable cost from an additional unit of quasi-fixed input ($-\partial G/\partial Z_k = F_k$) and explicitly captures the dependence on prices, stocks, output and the state of technology[4]. In the multiple quasi-fixed input case the left-hand side of equation (5) is not well defined. In addition, variable returns to scale prevent us from equating the residual measure of returns to fixed inputs, PY - G, where P is output price, with the shadow fixed cost, $\sum F_k Z_k$ (Morrison, 1988). Thus, for estimation purposes either it is assumed that shadow prices are proportional to ex-ante user's costs or equations (5) are omitted. Based on theoretical as well as empirical grounds, we decided for the second alternative.

[5] The relevant elasticities are reported in Appendix B. Being specified in terms of the same arguments as the estimating system (4), they explicitly encompasses the short run framework of analysis. In estimation, analytical derivatives and approximated standard errors are obtained through the TSP commands DIFFER and ANALYZ, respectively.

increase materializes in a higher degree of utilization of the relevant stock. Flexibilities, $\varphi_{kj}=\partial \ln F_k/\partial \ln Z_j$, say something about the long run behavior of quasi-fixed inputs, the pair being substitute (complement) when $\varphi_{kj}<0$ ($\varphi_{kj}>0$); on the other hand, the larger the absolute value of direct flexibility, φ_{kk}, the more rigid the latent demand for the k-th quasi-fixed input. Values greater than 1, e.g., suggest that an increase in Z_k makes its shadow value fall more than proportionally and so it does the profitability to increase the desired level of the quasi-fixed input.

Morrison (1985) has shown that scale effects in the short run are related to a measure of capacity utilization. The dual utilization index is defined as the ratio of shadow to total costs, $CU_C=C^*/C$ and represents the deviation of quasi-fixed inputs from their equilibrium levels in terms of total cost. Actually, under CRTS, short run flexibility and utilization index coincide:

$$\text{(6)} \qquad CU_C = \frac{C^*}{C} = \frac{G+\sum_k F_k Z_k}{G+\sum_k W_k Z_k} = \frac{C-\sum_k (W_k - F_k)Z_k}{C} = 1-\sum_k \varepsilon_{Ck} = \varepsilon_{CY}$$

where $d\ln Z_k/d\ln Y=1$, $\varepsilon_{CY}=\partial \ln C/\partial \ln Y$ indicates the relative change in total cost when an exogenous change of 1% in output occurs and factor fixity hampers full adjustment, $\varepsilon_{Ck}=\partial \ln C/\partial \ln Z_k=(W_k-F_k)Z_k/C$ is the cost flexibility with respect to stock k. When temporary and full equilibria coincide, $W_k=F_k$, hence $\varepsilon_{Ck}=0$ $\forall k$ and capacity is fully utilized, $CU_C=1=\varepsilon_{CY}$. *Viceversa*, ε_{Ck} may be positive or negative, according to Z_k being in excess or falling short of the desired level, respectively; over- ($CU_C>1$) or under-utilization ($CU_C<1$) will prevail depending on the algebraic contribution of each term. However, if scale economies and sub-optimal utilization interact, cost flexibility observed in the short run necessarily captures both effects. To disentangle the two contributions Morrison (1985) rewrites the long run cost flexibility, ε^L_{CY}, in the VRTS case; with homotheticity, the scale impact of all quasi-fixed inputs is the same and equal to the long run cost flexibility, resulting in:

$$\text{(7)} \qquad \varepsilon_{CY} = \varepsilon^L_{CY}\left(1-\sum_k \varepsilon_{Ck}\right) = \varepsilon^L_{CY} CU_C$$

where $\varepsilon^L_{CY}=d\ln C/d\ln Y=d\ln Z_k/d\ln Y$ is a local measure of scale economies evaluated at $C^*=C$. Thus, ε_{CY} is decomposed into two parts, a utilization component, CU_C, and a long run (inverse of) returns to scale component, ε^L_{CY}. Based on the parameter estimates, the latter may be derived empirically as $(\partial C/\partial Y)Y/C^*$ (Morrison, 1992).

Finally, concerning the role of innovations, we define the rate of technological progress (regress) as the percentage reduction (increase) in variable cost over time, $\varepsilon_{Gt}=\partial \ln G(.)/\partial t$. Generally, the effect of the passage of time on input i manifests itself in a non-neutral manner and such a bias is formalized by the rate of change in optimal factor proportions, $B_i=\partial \ln\omega_i/\partial t, \forall i$ (Binswanger, 1974). Recalling that the SGM demand functions are expressed in terms of input use, it can easily be seen that:

(8) $$B_i = \varepsilon_{it} - \varepsilon_{Gt}$$

where $\varepsilon_{it}=\partial \ln X_i/\partial t$ is the rate of change of input i over time. The semi-elasticities ε_{it}'s are not independent of one another (Kohli, 1994). Twice continuous differentiability and linear homogeneity properties of restricted cost function imply that $\partial G/\partial t=\Sigma_i(\partial^2 G/\partial t\partial W_i)W_i$. Dividing through by G and making use of ε_{Gt} and ε_{it} definitions, we get: $\varepsilon_{Gt}=\Sigma_i\omega_i\varepsilon_{it}$ and, consequently, $\Sigma_i\omega_i B_i=0$; meaning that technological change is a weighted sum of the semi-elasticities and, because of the adding-up of shares, biases cancel out. Technological change is defined to be input i-using ($B_i>0$), saving ($B_i<0$), or neutral ($B_i=0$), depending on whether relative change in the input use is larger, smaller or the same as the rate of cost reduction. On the other hand, overall neutrality implies that $B_i=0, \forall i$, i.e., all inputs are affected equiproportionally by technological change.

2.3 <u>Input technical efficiency</u>

The second part of our analysis concentrates on farm level efficiency. Based on Farrel (1957) definition, one can distinguish between output- and input-technical efficiency. The former reflects the failure to produce maximal output from a given quantity of inputs; the latter corresponds to a radial over-utilization of factors given output. The two concepts coincide if and only if constant returns to scale prevail (Färe and Lovell, 1978). Since we are dealing with a non-homogeneous technology the above one-to-one correspondence vanishes and this conveys far-reaching empirical implications. Input technical efficiency, e.g., does not enter the derived demands (4) but it appears only in the SGM restricted cost function. Namely, the farm specific cost frontier can be written as follows: $(1/b_f)G_f(.)$, where b_f, $0<b_f\leq 1$, reflects the cost-enhancing effect of input technical inefficiency (Atkinson and Cornwell, 1994) and f indexes farms.

Among the possible frontier approaches, we adopt the fixed-effect model. Farm effects are accounted for by specific intercepts, which reflect heterogeneity and consist, e.g., of input quality differences and management (Kumbhakar and Heshmati, 1995; Schmidt and Sickles, 1984). This should avoid the misspecification bias due to omitted variables, as well. Thanks to its simplicity, such an approach has been used quite extensively when examining panel data (Ahmad and Bravo-Ureta, 1995; Atkinson and Cornwell, 1994; Battese and Coelli, 1988; Bravo-Ureta and Rieger, 1991; Hallam and Machado, 1996). The advantages are that estimated relative efficiencies do not depend on restrictive distributional assumptions or independence between efficiency and the regressors, and are consistent as long as the number of time-series observations is large (Battese, 1992; Battese and Broca, 1997).

When the temporal dimension of the panel is substantial, however, the fixed-effect assumption may be incorrect (Ahmad and Bravo-Ureta, 1996; Kumbhakar and Hjalmarsson, 1993). In order to avoid such a risk the model can be extended either allowing efficiency to vary according to some parameterized function of time or including temporal dummies, which account for inter-period variations. We opted for the first alternative and chose a second-degree polynomial of time to approximate the efficiency path (Cornwell et al., 1990).

A two-step estimator is considered (Ahmad and Bravo-Ureta, 1995; Cornwell et al., 1990; Kumbhakar and Heshmati, 1995). In the first step, the minimized SGM variable cost is obtained through the parameters estimates of the demand system (4). After taking natural logarithms, the observed, $G_{ft}(.)$, and the estimated, $\hat{G}_{ft}(.) = \sum_i W_{ift} \hat{X}_{ift}(.)$, variable costs are related in the following way:

(9) $$\ln G_{ft}(.) = \ln \hat{G}_{ft} + \hat{\varepsilon}_{ft}$$

Being concerned with input technical efficiency, we assume that the error term of the cost function is composed as follows:

(10) $$\varepsilon_{ft} = u_f + v_{ft}$$

where $u_f=\ln(1/b_f)$, representing the farm effect, is restricted to be non-negative, and v_{ft} is the statistical noise, which in our case is heteroskedastic by construction. The stochastic frontier is the sum of the minimal cost function and the statistical noise. Secondly, given the residuals from the first step, $\hat{\varepsilon}_{ft} = \ln G_{ft} - \ln \hat{G}_{ft}$, time-varying efficiency parameters can be estimated by the least-squares procedure, as:

(11) $$\hat{\varepsilon}_{ft} = \sum_f \left(\gamma_f + \gamma_{1f} t + \gamma_{2f} t^2\right) D_f + v_{ft}$$

where v_{ft} is assumed independent and identically normally distributed with mean zero and finite covariance matrix[6]. The predicted values, $\hat{u}_{ft}$, in parentheses, are the basis for calculating farm level scores at each time t:

$$TE_{ft} = \min_{f}[\exp(\hat{u}_{ft})] / \exp(\hat{u}_{ft}) \tag{12}$$

The numerator of (12) is the least predicted value in each cross-section of the panel. That is, the minimum value of the efficiency indicator at time t is taken to be the best practice as well as the reference standard against which all other estimates are compared in that year.

3. Data

The original data set was taken from the Farm Accountancy Data Network (FADN). The sample used in this study consists of annual observations on 41 dairy farms from 1980 through 1992. The panel is balanced, meaning that the 41 farms stay in the sample for the entire period, and refers to specialized dairy or predominantly dairy farms with hired labor in the plain of Lombardia. This region constitutes the backbone of milk supply in Italy[7]. The observed holdings are medium to large size according to national standards[8].

The data set includes information on quantities and prices of one aggregate output and five categories of inputs. We calculate quantities by dividing the value of output and variable inputs by a farm-specific price index when available. In general, FADN source does not provide information on prices of intermediate inputs at farm-gate level, thus, farm-specific prices of the relevant categories are arrived at as Divisia indexes obtained by aggregating regional prices of the elementary components weighted by farm specific cost (revenue) shares (Helming, Oskam and Thijssen, 1993; Maietta, 1997). The base period is 1990.

Farm output is measured by the sales of milk, meat and crop at constant price. This aggregate measure does not comprise categories like self-produced inputs (feed grains, roughage, and so on) while it includes deficiency payments and other production subsidies.

As regards factor of production we consider three variable inputs: purchased feeds, other intermediate inputs, and hired labor, and two quasi-fixed inputs. Purchased feeds include aggregate outlays on concentrates, forages, feed grains and so on. The second category consists

6 The HETERO option of LSQ command causes TSP to compute standard errors which are consistent even in the presence of unknown heteroskedasticity (White, 1980).
7 Over the production years 1988/89 to 1994/95 the incidence of Lombardia on the delivered production of milk in Italy grew from 35.7% to 38.0% (Pieri and Rama, 1996).
8 For additional details about construction of these data the interested reader is referred to Maietta (1997).

of all the remaining intermediate inputs (fertilizer, pesticides, seed, fuel, energy, veterinary services, as well as the costs of repair and maintenance of capital equipment, etc.).

The quasi-fixed inputs comprise the flow of services from self-employed labor and capital. Capital is an aggregate measure of three categories, namely, livestock, machinery and building. We calculated quantities of livestock, machinery and building services by dividing the invested capital by a price index of these services. User's cost is defined as the sum of interest and depreciation of capital stock at farm level replacement value. The total working hours of self-employed and hired labor are calculated by dividing the relevant costs by the wage rate per hour. The number of hectares is available on each farm unit. Technological change is represented by a smooth time trend.

4. Empirical implementation and results

4.1 Specification tests and technology

After having introduced farm and time subscripts, a classical additive error term is appended to the behavioral equations (4) and parameters are estimated using iterative Zellner techniques[9] under the typical assumption that the error term v_{ift} for the i-th equation is i.i.d. across units f over all of the years t. At the outset, we maintain that no structural break occurred during the investigation period (1980-92). On the other hand, given that holdings are of different sizes, we allow for some heterogeneity in the i/o equation intercepts. By breaking down farms into three groups: small (17 farms less than 50 ha), medium (15 farms between 50 and 100 ha) and large (9 farms greater than 100 ha), we can test for the stability of the b_{ii} parameters. Based on the likelihood ratio (LR) test and a sample statistics[10] of 212.5, the null hypothesis of same intercepts had to be strongly rejected.

A further question is concerned with the existence of scale economies. Extending theorem 6 of Diewert and Wales to accommodate for quasi-fixed inputs, to test the overall returns to scale (CRTS) hypothesis in the long-run, we need to impose the following seven (N+M+2) parameter restrictions: H_0: $b_i=b_t=b_{YY}=c_{kY}=0$ (i=1,2,3; k=1,2). Given that the sample statistics is 208.7, which is well in excess of the critical value $\chi^2_{(7)}$=18.5 at the 1% level of significance, the CRTS hypothesis is decisively rejected. Next, we investigated whether the production function does exhibit any exogenous technical change, at all. Since ε_{Gt} represents the rate of cost diminution over time, the null hypothesis can be tested through the following seven

9 The command used is LSQ of TSP 4.4.

10 The parameters whose stability is tested are six - each input/output equation contains two dummies. The critical value is $\chi^2_{(6)}$=16.81 at 1% level.

(N+M+2) parameter restrictions: H_0: $b_{it}=b_t=b_{tt}=c_{kt}=0$ (i=1,2,3; k=1,2). The LR statistics is 86.5, meaning that this hypothesis is also rejected at 1% level of significance.

The estimated SGM restricted cost function[11] is monotonic in W and Y (non-decreasing) at all sample points, and in Z (non-increasing) at the approximation point[12]. Regarding the second-order properties, the estimated function is found to be (globally) concave in prices and (globally) convex in quasi-fixed inputs. Given the monotonicity results and the negative (positive) semidefiniteness of the estimated S (C) matrix, curvature criteria are satisfied globally by the proposed version.

Results will be analyzed by means of demand and shadow price elasticities as well as technological biases. Because differences over time and between groups are small we report only estimates at the panel mean, which represents the approximation point. Farm level scale economies and capacity utilization will be overviewed, too.

On the whole, the notable character emerging from table 1 is that input demands are much more responsive to output than prices. Hence, changes in factor proportions mainly depend on the level of production in the short run. Looking at price elasticities, one can observe that most coefficients are accurately estimated, direct effects are rightly signed and all responses are much smaller than unity, which suggests a rather rigid structure[13]. Cross effects show an overall substitutability, regardless of size and period.

We have that all inputs are normal, that is, non decreasing in output. However, because of variable returns, scale elasticities do not resemble each other; e.g., purchased feeds adjust more than proportionally (1.48) and about twice as much as hired labor (.7); other intermediate consumption being the least responsive (.43). Feeds and other inputs adjust consistently to both fixed inputs, though in opposite directions, while hired labor adjustment depends upon which stock is changing. In particular, family labor and capital are both substitute for purchased feeds. Feeds make up more than 45% of variable costs (table 3), hence an increased capacity, e.g., may reasonably be thought as the result of an investment decision aiming at self-producing forage and feed grains to substitute for the costly item. The two stocks and other inputs are complement; finally, self-employed farmers substitute for and capital services behave as complement of hired labor, in the long run. All these adjustments are modest, indeed, and within the range of price effects.

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11 The parameter estimates of the received version and the approximated standard errors available upon request.
12 Concerning the monotonicity in Z, we find 101 violations (about 1/5 of data points). It is the shadow price of capital which mostly happens to be negative (91 instances) with no apparent clustering round the particular year or farm. The violations disappear if we include the equations (5) in the estimating system.
13 Towards the end of the period, however, direct price elasticities tend to improve. In small farms, e.g., hired labor becomes elastic (-1.04). For the sake of brevity, farm group and selected period results are not presented. They are available upon request.

For the symmetry relationships attributable to the twice continuos differentiability of the cost function we have that: $\partial X_i/\partial Z_k$=-$\partial F_k/\partial W_i$. Such a comparative statics proposition can be re-phrased in terms of elasticities; namely, $\varepsilon_{ik}=-(\omega^*_i/\omega^*_k)\varphi_{ki}$, where ω^*_i and ω^*_k are the input shares on shadow cost C^*, and φ_{ki} gives the impact of W_i on the quasi-rent of stock k. Thus, quasi-fixed input demand elasticities and shadow price elasticities do share similar information. The substitutability between capital and purchased feeds (-.37), then, indicates that a rise in feed price makes capital quasi-rent appreciate. Consequently, the ratio of desired to actual levels of capital increases and, in the short run, the given capacity becomes scarse materializing in a higher degree of utilization (through variable input intensification) of capital.

As shown in table 2, the estimates confirm substitutability/complementarity relationships already discussed, based on the reciprocity criterion. E.g., since self-employed farmers tend to be a substitute for both purchased feeds and hired labor, an increase of their market prices makes the marginal productivity value of self-employed labor increase in the short run. The opposite is true with an axogenous change in the price of other inputs. Responses are normally higher for capital than self-employed labor. In particular, the quasi-rent of capital, and thus utilization, increases much more than proportionally with feed price (3.9), on the contrary wages (-.8) and especially other input price (-2.1) have negative impacts. Output flexibilities are not precisely estimated. So, from a statistical viewpoint, the role of output on shadow price might warily be taken close to nil for family labor and positive for capital. On the other hand, cross flexibilities of shadow prices seem indicate the two quasi-fixed inputs be weak complement.

In our framework of analysis, cost flexibility represents the combined effects of scale economies and sub-optimal capacity utilization. Table 4 gathers fam level estimates of ε_{CY}, ε^L_{CY} and CU_C; while figures 1 and 2 show the profile of the utilization index and its components, respectively, over time. Scale economies are evident for both groups. Output increases require a 42% smaller increase in variable costs in medium/large farms and allow around one third proportionate cost savings in small farms. This tendency is not as strong in the long run (somewhere between 13% and 10% according to farm groups) and it is estimated around 14% at the panel mean. The discrepancy is explainable with the fact that overall capacity is far from being fully utilized: more than one fourth (29%) is estimated to be in excess. Both quasi-fixed inputs contribute consistently to such a result, though at notably different levels: the excess is estimated around 9% for self-employed labor and a remarkable 20% for capital.

These figures give but a rough idea of the contradiction and the structural adjustment which dairy farmers in the panel, but very likely the whole sector in Italy, have to face under the milk quota system. The implementation of milk quotas dates back to 1983/84, but in Italy the system has become fully effective only at the end of the investigation period and this has had important consequences.

The situation has evolved markedly during the years. The ε_{Ck}'s slope monotonically downward, with capital always dominating but pacing faster (figure 2), such that its elasticity can halve (from .33 in 1980 to .16 in 1992) and come closer to that of self-employed labor (.08 in 1992). Consequently, the trend is towards reducing the overall excess of capacity, which makes CU_C move from about .55 at the beginning of the period to around .76 in 1992 (figure 1).

The rate of cost reduction, ε_{Gt}, is reported at the right bottom of table 3. It appears that variable cost has declined at 3.5% per annum[14]. The advancement of knowledge exerts a rather involved influence on i/o coefficients. Traditionally, the nature of innovations and the direction of biases are captured by the non-neutral changes in factor proportions. These estimates are presented in table 3. From the semi-elasticities, one can see that the passage of time alone has had a statistically significative impact on factor intensities, independently of both relative prices and scale adjustments. Bias in technical change turns out to be relatively using of other inputs and economizing in the remaining factors; with the labor saving effect (-.16) twice as much as that of purchased feeds (-.08). While the B_i's can clearly be of either sign, we generally expect the ε_{it}'s to be less than zero since their weighted average is negative and equal to ε_{Gt}. However, some ε_{it}'s may well be positive. This is the case with other intermediate inputs (.18), while both purchased feeds (-.11) and especially hired labor (-.19) register a steep downward sloped profile, ceteris paribus. In Kohli's terminology (1994), technological progress is ultra-biased against other inputs, in that not only it uses it in a relative sense but also because it makes its actual demand rise over time.

These findings are coherent with the results of table 1. Technical progress is remarkably intensive of that factor (other inputs) which is complement of the given capacity in the short run. As such, farmers adopt that technology whose implementation leads to variable cost savings.

4.2 Technical efficiency

Before commenting on the efficiency estimates we report on the testing procedures concerning the following features: time-variant vs. time-invariant fixed-effects and normality of residuals. Using the LR test, the null hypothesis of time-invariant efficiency, $H_0:\gamma_{11}=\gamma_{21}=...=\gamma_{1N}=\gamma_{2N}=0$, where N=41 is the number of farms, is rejected soundly - the estimated statistics being

14 Italian agriculture grew at 1.9% per annum over the same period (Pierani and Rizzi, 1994). The two studies share only the short run framework of analysis and differ in respect of type of data (panel vs. time-series), functional form (SGM vs. GL) and, of course, the case study: 41 dairy farms in the most dynamic and rich region vs. the whole agriculture in Italy.

$\chi^2_{(82)}$ = 303.35. This result substantiates that of Ahmad and Bravo-Ureta (1996) in that comparing alternative model specifications reached similar conclusions.

The hypothesis tests for zero skewness and zero excess kurtosis are based the following statistics:

$$(13) \qquad \begin{aligned} &(6n)^{-.5}\sum_f\sum_t e_{ft}^3 \\ &(24n)^{-.5}\sum_f\sum_t (e_{ft}^4 - 3) \end{aligned}$$

where e_{ft} are the normalized least squares residuals and n the number of observations in the panel. Under the null of normality, each of their squares will be asymptotically distributed as $\chi^2_{(1)}$ (Davidson and MacKinnon, 1993). The estimated statistics are found to be .28 and 90.81, respectively. This implies that the hypothesis of a symmetric distribution of efficiency ratings can be accepted but there is no evidence of zero excess kurtosis at 1% level of significance. Though it is often the case that residuals are not mesokurtic, the result suggest some caution in the following analysis.

To conserve space we report only average efficiency across farm groups[15]. The estimates in table 6 indicate that the panel efficiency is .66. On average, then, an identical level of output could have been achieved with approximately 34 percent fewer resources if farms would have operated technically resembling the best practice. It is common opinion that farmers who use today's technology more efficiently are likely to persist in their pre-eminence, but that does not necessarily follow. In our case, the reference happens to be always the same medium/large farm but the last two years when the most efficient farm is a small one.

Our measures of average efficiency tend to be lower than those reported by other studies of the dairy sector using a variety of stochastic frontiers (Bravo-Ureta, 1986; Bravo-Ureta and Rieger, 1991; Kumbhakar and Hjalmarsson, 1993; Kumbhakar and Heshmati, 1995). The validity of the assertion rests on the comparability of the case studies, however the result seems to support that of Hallam and Machado (1996) and Ahmad and Bravo-Ureta (1996), who find that the more restrictive is the estimator in terms of necessary assumptions, the higher is the efficiency estimates it provides. In their study of Portoguese dairy farms, Hallam and Machado obtain average efficiency measures ranging from 56 per cent (within) to 88 per cent (variance components). Ahmad and Bravo-Ureta, using an unbalanced panel of 96 Vermont dairy farmers for the 1971-84 period, opted for the time-varying fixed-effect model which yielded an average

15 The estimates of least-squares parameters and farm level effects are available from the authors upon request.

technical efficiency of 77%.

The panel variation ranges from a very low of .47 to a high of 1.0, meaning that the least efficient farm achieves only 47% of the output of the most efficient one, ceteris paribus. In fact, covariance analysis commonly produces such large differences in comparative efficiencies (Dawson et al., 1991). In our panel, small farms seems slightly less efficient as well as less disperse than medium/large holdings, the size being defined in terms of hectares. The breaking down of the investigation period, before and after the implementation of the quota system in the dairy sector of the UE, does not seem to produce appreciable differences. However, looking at figure 3 emerges some evidence of smooth variation over the years, with a notable break occurring at the turn of the decade when the efficiency rating reverses. As consequence one can observe a systematic improvement in the efficiency over the second half of the eighties and a sudden worsening thereafter. This has been particularly true for the highest efficiency class, as if the consequences of an unclear adoption of the quota system during the second half of the eighties suddenly coupled with the enforcement of individual quotas have hurt medium/large farms more than small farms.

The frequency distribution of technical efficiency for selected periods is presented in table 5. A look at the table shows that the percentage of farms in the class 50% and below is 1.7, whereas only 9.4% is in the class 80% and above. The bulk of farms, around 88% of the panel, is in the efficiency class 50 to 80%. There is some similarity in the distribution over time, except in the middle class. The percentage of farms in the efficiency class 60 to 70% has increased from 38 percent to 48 percent over the period 1980/84 to 1985/92. The percentage of farms in the highest efficiency classes is about constant between the two periods; whereas the percentage in the efficiency class 50% and below during 1985/92 is about double of that during 1980/84.

5. Concluding comments

The objective of the paper is to contribute to the literature on flexible functional forms. Drawing from Diewert and Wales (1987), we propose a short term specification of the SGM cost function which allows for quasi-fixed factors of production and variable returns to scale so that the role of temporary equilibrium and economies of scale can be adequately investigated. The modified version is flexible, parsimonious, and globally curvature correct.

A two-stage procedure is used to estimate first the parameters of input demands derived from cost minimizing behavior of the individual farms and then farm level technical efficiency. A balanced panel of 41 specialized dairy farms in the plain of Lombardia observed over the years 1980 to 1992 serves as case study. The farming technology, which consists of one aggregate output, three variable inputs (purchased feed, other intermediate consumption, hired labor), two quasi-fixed inputs (self-employed labor and capital), is analyzed through a set of price elasticities of both variable inputs and shadows prices. In addition, cost flexibility is decomposed into scale economies and overall capacity utilization.

In the short-term, purchased feeds, other inputs and hired labor are found to be price-inelastic, substitutes of one another, and much more responsive to scale adjustments than to market prices. There exist scale economies and overall excess of the given capacity for both small and medium/large farms; both self employed labor and capital are under under-utilized, although the tendency is towards reducing the excess of capacity. We found the rate of cost reduction to be 3.5% per year at the panel mean. Technological bias is also examined. The estimates indicate that the non-neutral changes in factor proportions turn out to be in favor of hired labor and purchased feeds but against other inputs.

This study reports also measures of farm level technical efficiency based on the fixed effects model. In the second stage, no distributional assumptions are required to separate input technical efficiency out of the estimated residuals of the first-stage. Farms effects are assumed to vary according to a second degree polynomial of time. The individual scores reflect resource over-utilization in production activity as compared to the most efficient farm in the sample.

We found that input technical efficiency ranges between 47 and 100 percent with a panel average of 66 percent, i.e., the level of output produced in the period 1980/92 could have been achieved with approximately one third fewer resources if all farms would have operated efficiently, in a relative sense. The result might be used as measure of a disappointing technical performance after milk quotas, but to certain extent is also the reflection of the approach chosen, as suggested by previous studies (Hallam and Machado, 1996; Ahmad and Bravo-Ureta, 1996). There is little evidence that larger farms tend to be more efficient, which of course may depend on the hectare based definition of size. Estimates show that small farms are only slightly less efficient as well as less disperse than medium/large farms. There is, however, some evidence of smooth variation of efficiency over the years, with a notable break at the turn of the decade when thereafter, the rating reverses and small farms become more efficient. Another finding of this study is the narrow spread of farm efficiency. From the frequency distribution for selected periods it emerges that around 88 percent of the farms is concentrated in the efficiency class 50 to 80% with a stable distribution over time.

Table 1: *Variable input elasticities (computed at the sample mean - approximated standard errors in parenthesis)*

All farms, 1980/92	Feeds	Other inputs	Hired labor	Output	Family labor	Capital
Feeds	-.312 (.144)	.162 (.134)	.150 (.039)	1.483 (.041)	-.116 (.028)	-.368 (.038)
Other inputs	.237 (.196)	-.354 (.192)	.117 (.049)	.430 (:046)	.129 (.032)	.288 (.041)
Hired labor	.321 (.084)	.171 (.071)	-.492 (.066)	.699 (.058)	-.354 (.040)	.161 (.055)

Table 2: *Shadow price flexibilities (computed at the sample mean - approximated standard errors in parenthesis)*

All farms, 1980/92	Feeds	Other inputs	Hired labor	Output	Family labor	Capital
Family labor	.601 (.106)	-.460 (.197)	.859 (.162)	-.298 (.451)	-.642 (.348)	.217 (.051)
Capital	3.853 (1.919)	-2.066 (1.331)	-.787 (.632)	.889 (:498)	.437 (.245)	-1.974 (1.106)

Table 3: *Cost shares, technological biases and rates of change of inputs (computed at the sample mean - approximated standard errors in parenthesis)*

All farms, 1980/92	ω_i	B_i	ε_{it}
Feeds	.465 (005)	-.076 (.023)	-.111 (.029)
Other inputs	.318 (.004)	.218 (.029)	.184 (.033)
Hired labor	.217 (.003)	-.157 (.037)	-.191 (.043)
Weighted sum	1	0	-.035 (.018)

Table 4: *Cost-based measures of scale effects, capacity utilization and elasticities of utilization at farm level (computed at the sample mean - approximated standard errors in parenthesis)*

1980/92	ε_{CY}	$\varepsilon^{L}_{CY} = \eta$	CU_C	ε_{CZ_1}	ε_{CZ_2}
# 1	.753 (.024)	.942 (.033)	.799 (.025)	.085 (.024)	.116 (.009)
# 2	.568 (.029)	.911 (.039)	.623 (.033)	.203 (.031)	.174 (.011)
# 3	.660 (.040)	.964 (.039)	.685 (.045)	.211 (.043)	.104 (.011)
# 4	.672 (.028)	.893 (.046)	.753 (026)	072 (.023)	.175 (.012)
# 5	.645 (.024)	.923 (.037)	.698 (.026)	.079 (.022)	.223 (.015)
# 6	.649 (.021)	.913 (.022)	.710 (.023)	.141 (.021)	.149 (.012)
# 7	.608 (.019)	.888 (.020)	.685 (.021)	.099 (.017)	.216 (.014)
# 8	.628 (.018)	.886 (.018)	.709 (.017)	.120 (.016)	.171 (.009)
# 9	.661 (.035)	.964 (.058)	.685 (.038)	.144 (.033)	.171 (.018)
# 10	.612 (.019)	.838 (.024)	.731 (.016)	.108 (.014)	.161 (.009)
# 11	.568 (.022)	.783 (.028)	.726 (.016)	.075 (.013)	.199 (.010)
# 12	.636 (.022)	.914 (.022)	.695 (.024)	.133 (.020)	.172 (.016)
#13	.727 (.025)	.954 (.025)	.762 (.027)	.129 (.024)	.109 (.013)
#14	.579 (.019)	.898 (.019)	.644 (.020)	.100 (.016)	.256 (.016)
# 15	.736 (.018)	.876 (.018)	.840 (.018)	.042 (.015)	.118 (.012)
# 16	.635 (.023)	.887 (.022)	.716 (.024)	.157 (.021)	.128 (.015)
# 17	.634 (.019)	.846 (.019)	.749 (.018)	.094 (.015)	.157 (.013)
# 18	.661 (.017)	.859 (.019)	.770 (.018)	.035 (.011)	.196 (.014)
# 19	.624 (.018)	.875 (.019)	.714 (.019)	.129 (.014)	.158 (.015)
# 20	.517 (.027)	.745 (.038)	.693 (.020)	.082 (.016)	.225 (.014)
# 21	.666 (.017)	.865 (.015)	.770 (.019)	.068 (.014)	.162 (.016)
# 22	.573 (.021)	.855 (.035)	.671 (.021)	.125 (.016)	.205 (.015)
# 23	.533 (.022)	.856 (.042)	.623 (.023)	.142 (.018)	.236 (.016)
# 24	.647 (.020)	.897 (.018)	.721 (.022)	.129 (.016)	.151 (.017)
# 25	.519 (.035)	.708 (.044)	.734 (.018)	.023 (.006)	.243 (.016)
# 26	.695 (.019)	.845 (.020)	.823 (.018)	.050 (.013)	.127 (.014)
# 27	.641 (.019)	.837 (.021)	.766 (.020)	.077 (.013)	.157 (.017)
# 28	.546 (.028)	.864 (.059)	.631 (.030)	.188 (.028)	.181 (.015)
# 29	.586 (.019)	.840 (.026)	.698 (.019)	.100 (.014)	.203 (.016)
# 30	.536 (.026)	.773 (.037)	.693 (.022)	.082 (.016)	.225 (.017)
# 31	.519 (.024)	.887 (.049)	.585 (.027)	.164 (.023)	.251 (.017)
# 32	.606 (.020)	.842 (.027)	.720 (.020)	.071 (.014)	.210 (.016)
# 33	.589 (.024)	.853 (.045)	.691 (.027)	.155 (.023)	.154 (.016)
# 34	.347 (.056)	.535 (.078)	.649 (.028)	.082 (.021)	.269 (.017)
# 35	.689 (.018)	.874 (.017)	.788 (.020)	.056 (.013)	.156 (.017)
# 36	.564 (.023)	.906 (.015)	.622 (.027)	.065 (.013)	.313 (.027)
# 37	.458 (.040)	.666 (.053)	.687 (.025)	.067 (.018)	.246 (.018)
# 38	.564 (.022)	.828 (.036)	.681 (.024)	.117 (.017)	.203 (.019)
# 39	.554 (.024)	.817 (.041)	.678 (.026)	.119 (.020)	.203 (.019)
# 40	.567 (.027)	.774 (.035)	.732 (.026)	.087 (.017)	.181 (.021)
# 41	.551 (.027)	..864 (.055)	.639 (.031)	.124 (.025)	.237 (.022)
Small farms	.664 (.20)	.904 (.020)	.735 (.021)	.101 (.018)	.165 (.012)
Medium/ large farms	.581 (.021)	.827 (.029)	.703 (.021)	.093 (.014)	.204 (.017)
All farms	.612 (.018)	.862 (.021)	.710 (.019)	.090 (.013)	.201 (.016)

Table 5: *Frequency distribution of technical efficiency for selected periods*

Efficiency levels (%)	1980/92 percent	1980/84 percent	1985/92 percent
Below 50.0	1.7	1.0	2.1
50.1-60.0	27.9	32.7	25.0
60.1-70.0	44.3	38.0	48.2
70.1-80.0	16.7	19.0	15.2
80.1-90.0	5.3	4.9	5.5
90.1-100.0	4.1	4.4	4.0
Total	100	100	100
Std. dev.	.10	.11	.10

Table 6: *Relative efficiency scores for farm groups*

Period	1980/92			
Group	**Mean**	**Std. dev.**	**Min**	**Max**
Small farms	.66	.09	.48	1.00
Medium/large farms	.67	.11	.47	1.00
All farms	.66	.10	.47	1.00

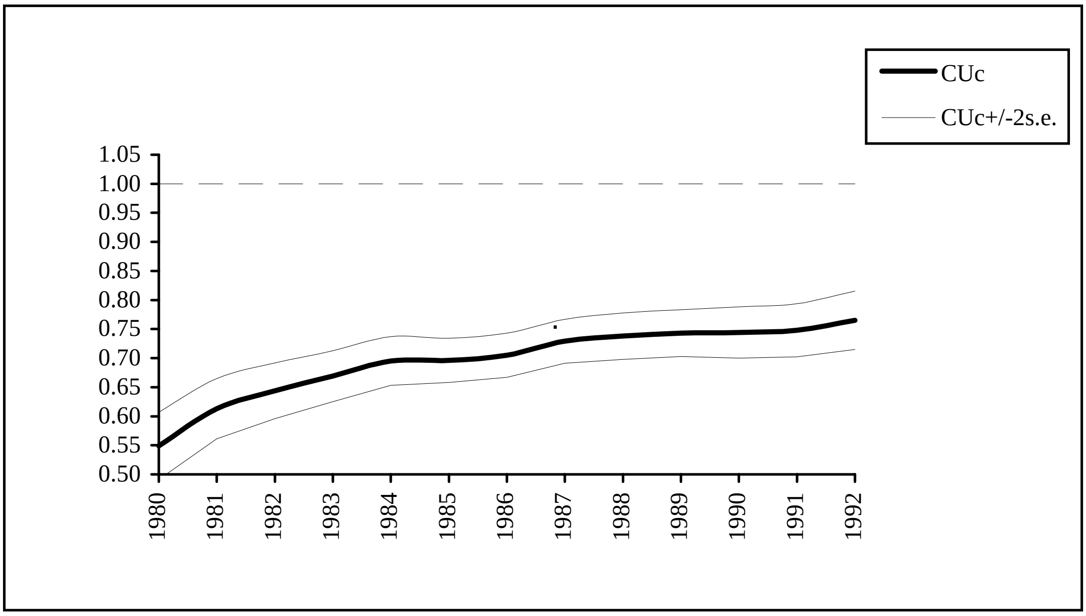

Figure 1: *Capacity utilization over time (computed at the sample mean)*

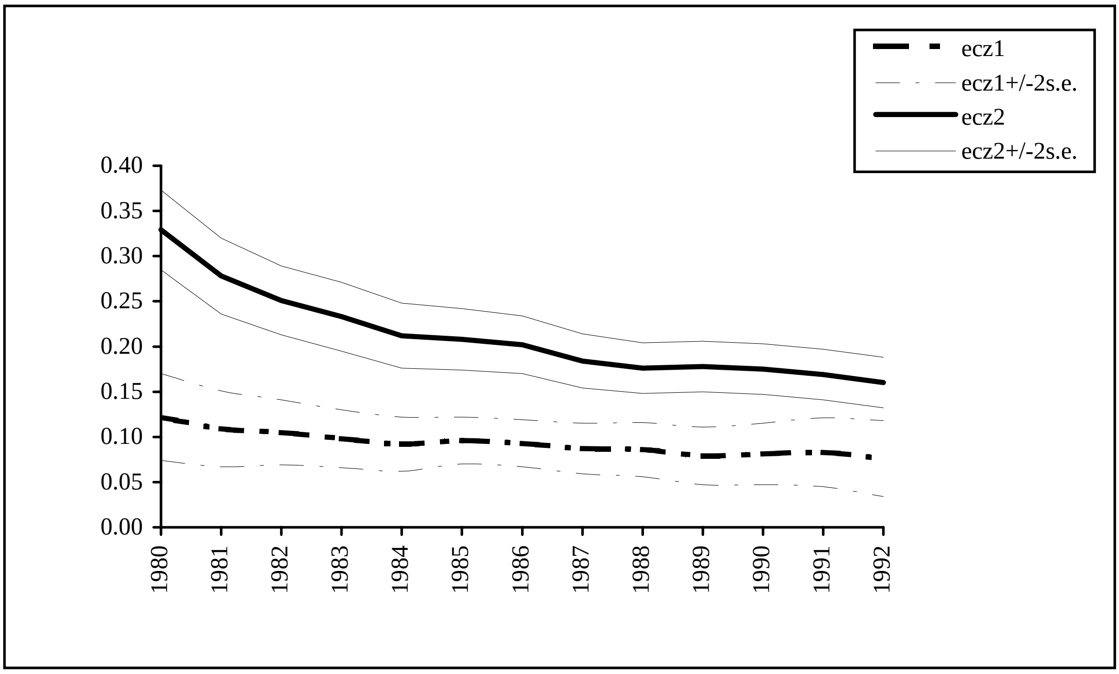

Figure 2: *Family labor (*ε_{CZ_1}*) and capital (*ε_{CZ_2}*) elasticities of utilization over time (computed at the sample mean)*

Figure 3: *Technical efficiency scores over time (average by group)*

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Appendix A

In general, a twice-continuously differentiable cost function *C(.)* can provide a second-order differential approximation to the unknown function $C^*(.)$ at a point (Y^*,W^*,t^*) if and only if the level, (N+2) first derivatives, and $(N+2)^2$ second partial derivatives of $C^*(.)$ and *C(.)* coincide at (Y^*,W^*,t^*). Considering that linear homogeneity in *W* and simmetry properties imply (N+3) + (N+2)(N+1)/2 restrictions, *C(.)* can be defined as flexible at the approximation point if it contains enough free parameters to measure at least N(N+1)/2 + 2N + 3 effects (Diewert, 1976). Adapting this definition to the enlarged argument list, a twice continuously differentiable restricted cost function *G(.)* is flexible at the point (Y^*,W^*,Z^*,t^*) if and only if it contains enough free parameters so that the following $1+(N+M+2)+(N+M+2)^2$ equations can be satisfied:

$$\begin{aligned} & G(*) = G^*(*) \\ \text{(A.1)} \quad & \nabla G(*) = \nabla G^*(*) \\ & \nabla^2 G(*) = \nabla^2 G^*(*) \end{aligned}$$

where $(Y^*,W^*,Z^*,t^*)\equiv(*)$ and $(Y,W,Z,t)\equiv(.)$, ∇ denotes the column vector of the first order partial derivatives and ∇^2 the matrix of second order partial derivatives with respect to (.). However, the linear homogeneity property in *W* and the Euler's theorem on homogeneous functions imply the following (M+N+3) restrictions on first and second derivatives of *G*:

$$\begin{aligned} & W'\nabla_W G(*) = G(*) \\ & W'\nabla^2_{WW} G(*) = 0 \\ \text{(A.2)} \quad & W'\nabla^2_{WY} G(*) = \nabla_Y G(*) \\ & W'\nabla^2_{Wt} G(*) = \nabla_t G(*) \\ & W'\nabla^2_{WZ} G(*) = \nabla_Z G(*) \end{aligned}$$

where the apostrophe stays for transposition, and $\nabla_W, \nabla^2_{WW}, \nabla^2_{WY}, \nabla^2_{Wt}, \nabla^2_{WZ}$ indicate properly dimensioned relevant partitions of ∇ vector and ∇^2 matrix, respectively. Furthermore, the twice continuously differentiability in all its arguments and Young's theorem imply the following (N+M+2)(N+M+1)/2 simmetry restrictions:

$$\text{(A.3)} \quad \nabla^2 G(*) = \nabla^2 G(*)'$$

Hence in order to be flexible, a twice continuously differentiable (homogeneous in *W*) *G(.)* must contain at least $[1 + (N+M+2) + (N+M+2)^2] - [(M+N+3) + (N+M+2)(N+M+1)/2] = (N+M)(N+M+1)/2 + 2(N+M) + 3$ free parameters. Now, following theorem 11 of Diewert and Wales (1987), it can be shown that the SGM defined by (2) and (3) with $S'W^*=0$, is a flexible (homogeneous in *W*) restricted cost function at the point (*) provided that $W^*>>0$, $\theta' W^*\neq 0$, $\alpha' W^*\neq 0$, $\beta' W^*\neq 0$, $\gamma' W^*\neq 0$, $\delta' W^*\neq 0$, $\lambda' W^*\neq 0$, $\eta' W^*\neq 0$. The parameter vectors θ, along with α, β, γ, δ, λ, η are assumed to be exogenously given. The remaining parameters s_{ih}, b_{ii}, b_i, b_{it}, b_t, b_{YY}, b_{tt}, d_{ik}, c_{kY}, c_{kt}, and c_{jk} are to be estimated. Thus, recalling that $\sum_h s_{ih}=0\ (\forall i)$, $s_{ih}=s_{hi}$, *and* $c_{jk}=c_{kj}$, there are (N+M)(N+M+1)/2 + 2(N+M) + 3 free parameters in the proposed SGM restricted cost function - just enough for it to be flexible at the point (Y^*,W^*,Z^*,t^*).

On the other hand, following theorem 10 of Diewert and Wales, the *G(.)* is globally concave in variable input prices *W* if *S* is negative semidefinite, and globally convex in quasi-fixed stocks *Z* if $C\equiv\{c_{jk}\}$ is positive semidefinite.

Appendix B

In the following we report the analytical expressions of some relevant elasticities we considered in our study:

(B.1) $$\varepsilon_{ij} = \frac{\partial \ln X_i}{\partial \ln W_j} = \frac{W_j}{X_i}\left\{\frac{s_{ij}}{\theta' W} - \frac{(S^{(i)}\theta_j + S^{(j)}\theta_i)W}{(\theta' W)^2} + \theta_i \theta_j \frac{W' SW}{(\theta' W)^3}\right\}$$

where $S^{(i)}$ is the *i-th* row of the S matrix.

(B.2) $$\varepsilon_{iY} = \frac{\partial \ln X_i}{\partial \ln Y} = \frac{Y}{X_i}\left\{\left[\frac{S^{(i)}W}{\theta' W} - \frac{\theta_i}{2}\frac{W' SW}{(\theta' W)^2}\right] + b_{ii} + b_{it}t + 2\beta_i b_{YY} Y + \gamma_i b_{tt} t^2 + \delta_i \sum_k c_{kY} Z_k - \frac{\eta_i}{2}\sum_j \sum_k c_{jk} \frac{Z_j Z_k}{Y^2}\right\}$$

(B.3) $$\varepsilon_{it} = \frac{\partial \ln X_i}{\partial t} = \frac{1}{X_i}\left\{b_{it} Y + \alpha_i b_t + 2\gamma_i b_{tt} tY + \lambda_i \sum_k c_{kt} Z_k\right\}$$

(B.4) $$\varepsilon_{Gt} = \frac{\partial \ln G}{\partial t} = \frac{1}{G}\left\{\sum_i b_{it} W_i Y + b_t(\alpha' W) + 2b_{tt}(\gamma' W)tY + \sum_k c_{kt}(\lambda' W) Z_k\right\}$$

(B.5) $$\varepsilon_{GY} = \frac{\partial \ln G}{\partial \ln Y} = \frac{Y}{G}\left\{g(W) + \sum_i b_{ii} W_i + \sum_i b_{it} W_i t + 2b_{YY}(\beta' W)Y + b_{tt}(\gamma' W)t^2 + \sum_k c_{kY}(\delta' W) Z_k - .5\sum_j \sum_k c_{jk}(\eta' W)\frac{Z_j Z_k}{Y^2}\right\}$$