INPUT SUBSTITUTION IN THE SPANISH FOOD INDUSTRY

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Abstract

Firm panel data sets over the period 1993 to 2002 are used to estimate translog production functions with labour, capital and material inputs for 9 Spanish food industries. To tackle the endogeneity of the regressors, the generalized method of moments estimations is employed. The specification tests reject the instrument variables only for 1 out of 9 estimates. The remaining 8 industries show evidence of homogeneity and constant returns to scale. Only one industry exhibits complete separability of all pairs of factors and thus translog is preferred to Cobb-Douglas specification for 7 industries. Substitutability and complementarity between production factors in response to price changes are studied through Morishima and Shadow elasticities. Substitutability between labor and capital and complementarity between labor and materials are the most common relationships.

Keywords: translog; elasticity of substitution; generalized method of moments; returns to scale
JEL classification: C23, D24, L66

1 Introduction

A production level can be reached with different input alternatives, so firms can vary factor usages in response to price or output changes. These effects on quantities demanded of factors are the main concern of the traditional theory of derived demand.

Inputs can be characterized as either substitutes or complements depending on how they enter the production function. For example, if labour and capital are substitutes a decrease of capital price could entail the utilization of more capital and less labour, but if they are complements the effect would be an increase of both inputs. Elasticities of substitution provide information upon the direction and the degree of difficulty of these adjustments. In addition, properties such as homogeneity or constant returns to scale allow to know the expansion path of the firms, i.e. the curvature of isoquants will be independent of the level of output if homogeneity condition holds. On the other hand, the property of separability between inputs also contributes to improve the knowledge upon the sequential process of incorporating and replacing factors of production.

The aim of this work is to characterize the structure of input usages in the Spanish food industries at a microeconomic level. Perhaps cost functions would be the most appropriate way to study the response to price changes but information on prices at firm level is not available. In contrast, a huge quantity of data on inputs used and outputs obtained by firms can be extracted from balance sheets. For this reason, translog production functions, which do not restrict the issues mentioned above (homogeneity, constant returns to scale and separability), are specified with three factors of production, labour, capital and materials.

A problem related with direct single-equation estimation is that endogeneity of inputs could cause correlation between the regressors and the error term. However the panel data structure allows to use instrumental variable techniques that accounts for this and are robust to heteroskedasticity and autocorrelation.

The remainder of the work is organized as follows. Section 2 presents the translog specification for a production function in a panel data context as well as its properties. Section 3 deals with different measures of substitutability , such as Allen, Morishima and Shadow elasticities of substitution. Section 4 briefly outlines the data sets, Section 5 shows and comments the estimates and the tests and finally Section 6 concludes.

2 The translog production function

It is assumed firms operate under perfect competition, in both output (y) and input (x_j) markets, and they use a common technology that can be represented by the production function

$$y = f(x_1, \cdots, x_j, \cdots, x_J). \tag{1}$$

It can be specified using a flexible functional form such as the well known and widely used transcendental logarithmic (translog) which provides a local second-order approximation to any production frontier (Christensen et al., 1973). Adopting a panel data notation with subscript j $(1, \ldots, J)$ for inputs, i $(1, \ldots, I)$ for firms and t $(1, \ldots, T)$ for time periods, and adding individual (μ_i) and time (λ_t) effects, this function can be written as

$$\ln y_{it} = \sum_j \beta_j \ln x_{jit} + \frac{1}{2} \sum_j \sum_k \beta_{jk} \ln x_{jit} \ln x_{kit} + \mu_i + \lambda_t + \nu_{it} \tag{2}$$

where the β's are parameters to be estimated, taking into account the symmetry condition $\beta_{jk} = \beta_{kj}$. In contrast to other forms, the translog imposes neither elasticities to be fixed throughout the input space nor separability of production factors. But it is necessary to verify some basic properties of production functions at each point. So, positive monotonicity can be checked by means of the output elasticities to input changes at each point it:

$$\epsilon_{jit} = \frac{\partial f}{\partial x_j} \frac{x_j}{f} = \beta_j + \sum_k \beta_{jk} \ln x_{kit} > 0 \quad \forall j, i, t \tag{3}$$

On the other hand, convexity of the space requires a major computational effort since it demands that the successive principal minors of the Hessian bordered by the partial derivatives ($f_j = \frac{\partial f}{\partial x_j}$) to be alternatively negative and positive.

Once proved the function is well behaved over the data set, other properties of production technology, such as homogeneity, constant returns to scale or separability of production factors, can be tested.

The function f is homogeneous of degree h if

$$f(rx_1, rx_2, \cdots, rx_J) = r^h f(x_1, x_2, \cdots, x_J) \quad \forall r \neq 0$$

or alternatively by Euler's theorem if

$$f_1 x_1 + f_2 x_2 + \cdots + f_J x_J \equiv h f(x_1, x_2, \cdots, x_J) \tag{4}$$

In the translog function $f_j x_j = (\beta_j + \sum_k \beta_{jk} \ln x_{kit}) f$, so the first term of equation (4) can be rearranged to obtain

$$(\sum_j \beta_j + (\sum_k \beta_{1k}) \ln x_{1it} + \cdots + (\sum_k \beta_{Jk}) \ln x_{Jit}) f$$

and Euler condition holds if

$$\sum_k \beta_{jk} = 0 \quad \forall j \tag{5}$$

If that is so, the specified translog function is homogeneous of degree $h = \sum_j \beta_j$, and constant returns to scale are observed if, in addition, the restriction

$$\sum_j \beta_j = 1 \tag{6}$$

is fulfilled.

Separability has to be with the possibility to form groups of inputs that are independent in relation with their purchases. A set of inputs is said to be separable from the remaining production factors if the marginal rates of technical substitution between pairs of inputs in that group are independent of the inputs outside the group. The mathematical condition for x_j, x_k to be separable from x_m is expressed as

$$f_j f_{km} - f_k f_{jm} = 0 \tag{7}$$

which in the translog case takes the form (Berndt and Christensen, 1973)

$$\epsilon_j \beta_{km} - \epsilon_k \beta_{jm} = 0 \tag{8}$$

or equivalently

$$\beta_j \beta_{km} - \beta_k \beta_{jm} + (\beta_{j1}\beta_{km} - \beta_{k1}\beta_{jm}) \ln x_{1it} + \cdots + (\beta_{jJ}\beta_{km} - \beta_{kJ}\beta_{jm}) \ln x_{Jit} = 0 \tag{9}$$

In relation to these expressions, Denny and Fuss (1977) distinguish several kinds of pairwise separability of x_j and x_k from x_m. The null hypothesis for approximate weak separability is

$$\beta_j \beta_{km} - \beta_k \beta_{jm} = 0 \tag{10}$$

whereas exact weak separability involves in addition more non-linear restrictions

$$\frac{\beta_{j1}}{\beta_{k1}} = \frac{\beta_{j2}}{\beta_{k2}} = \cdots = \frac{\beta_{jJ}}{\beta_{kJ}} \tag{11}$$

for any x_j, x_k inside the group. Pairwise strong separability of x_j and x_k from x_m requires the linear constraints

$$\beta_{km} = \beta_{jm} = 0 \tag{12}$$

3 Measuring substitution between production factors

The elasticity of substitution, introduced by Hicks (1932) for a two-input production function, quantifies the curvature of the isoquant and is defined as the elasticity of the input ratio in relation to the marginal rate of substitution:

$$\sigma_{jk} = \frac{d(x_j/x_k)}{d(f_k/f_j)} \frac{f_k/f_j}{x_j/x_k} \tag{13}$$

Since the marginal rate of substitution is equal to the ratio of input prices $(-\frac{P_k}{P_j})$ at the minimum cost combination of inputs under perfect competition, the elasticity of substitution can be seen as a proportional rate of change in the input ratio with respect to the input price ratio. Thus, substitutability between inputs is characterized by positive values of the elasticity of substitution, as an increase (decrease) of the price ratio produces an increase (decrease) of the input ratio, and complementarity by the reverse.

Several expressions have been proposed to generalize this concept to the case of more than two inputs. The Allen partial elasticity of substitution expressed in terms of the production function can be shown to be [1]:

$$\sigma^A_{jk} = \frac{\sum_j x_j f_j}{x_j x_k} \frac{F_{jk}}{F} \tag{14}$$

with F being the bordered Hessian determinant and F_{jk} the cofactor associated with f_{jk}. Since $f_{jk} = f_{kj}$, the bordered Hessian and σ^A_{jk} are symmetric. Allen expression measures the change of one input in response to the change in the price of another, maintaining output and other prices fixed, and is classified as one-factor-one-price elasticity of substitution (following Mundlak, 1968; Chambers, 1988). It is the most popular elasticity of substitution and has been reported in many empirical studies on factor substitution. However, Blackorby and Russell (1989) demonstrate that Allen elasticity does not succeed to grip the concept of curvature or ease with which one input can be substituted for another since it is sensitive to variations in other input prices. Thus, it has no meaning from a quantitative point of view, and qualitatively it produces the same classification than that of the cross-price elasticity. They present Morishima elasticity as the exact measure of curvature in the sense of the Hick's two-dimensional definition. It can be mathematically expressed as:

$$\sigma^M_{jk} = \frac{f_k}{x_j}\frac{F_{jk}}{F} - \frac{f_k}{x_k}\frac{F_{kk}}{F} = \frac{f_k x_k}{\sum_j f_j x_j}(\sigma^A_{jk} - \sigma^A_{kk}) \tag{15}$$

Morishima elasticities are not symmetric ($\sigma^M_{jk} \neq \sigma^M_{kj}$). It is worth to note that two inputs classified as Allen substitutes ($\sigma^A_{jk} > 0$) are always Morishima substitutes ($\sigma^M_{jk} > 0$) as can be seen in the final part of (15): $\sigma^A_{jk} > 0$ leads to $\sigma^M_{jk} > 0$, provided $\sigma^A_{kk} \leq 0$. But two Allen complements can be Morishima substitutes if $\left|\sigma^A_{kk}\right| > \left|\sigma^A_{jk}\right|$.

Chambers (1988) also thinks Morishima elasticity to be a more economically relevant concept since it gives the exact variation of the input ratio in response to a change in an input price (two-factor-one-price elasticity of substitution). But he proposes the so-called Shadow elasticity of substitution (McFadden, 1963) as a two-factor-two-price elasticity of substitution and therefore a closer candidate to the initial Hicksian idea. It can be expressed as a weighted average of two Morishima elasticities with weights equal to input cost shares. In a cost minimization environment, these weights might be replace by the estimates of input-output elasticity shares ($s_j = \frac{\epsilon_j}{\sum_j \epsilon_j}$), since input prices become equal to their marginal products. Shadow elasticity of substitution would take the form:

$$\sigma^S_{jk} = \frac{s_j}{s_j + s_k}\sigma^M_{jk} + \frac{s_k}{s_j + s_k}\sigma^M_{kj} \tag{16}$$

[1] In the translog case, an easier computational expression is obtained (Berndt and Christensen, 1973): $\sigma^A_{jk} = \frac{G_{jk}}{G}$ where G is determinant of

$$\begin{pmatrix} 0 & \epsilon_1 & \epsilon_2 & \cdots & \epsilon_J \\ \epsilon_1 & b_{11} + \epsilon_1^2 - \epsilon_1 & b_{12} + \epsilon_1\epsilon_2 & \cdots & b_{1J} + \epsilon_1\epsilon_J \\ \epsilon_2 & b_{12} + \epsilon_1\epsilon_2 & b_{22} + \epsilon_2^2 - \epsilon_2 & \cdots & b_{2J} + \epsilon_2\epsilon_J \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \epsilon_J & b_{1J} + \epsilon_1\epsilon_J & b_{2J} + \epsilon_2\epsilon_J & \ldots & b_{JJ} + \epsilon_J^2 - \epsilon_J \end{pmatrix}$$

and G_{jk} the jk cofactor.

Of course, Shadow elasticity of substitution can be put in terms of partial Allen elasticities (Sato and Koizumi, 1973):

$$\sigma^S_{jk} = \frac{s_j s_k (2\sigma^A_{jk} - \sigma^A_{jj} - \sigma^A_{kk})}{(s_j + s_k)} \tag{17}$$

Taking into account zero-degree homogeneity in factor prices, $\sum_k s_k \sigma^A_{jk} = 0$, they give an equivalent expression obtained by eliminating own elasticities:

$$\sigma^S_{jk} = (s_j + s_k)\sigma^A_{jk} + \frac{s_k}{s_j + s_k} \sum_{m \neq j,k} s_m \, \sigma^A_{jm} + \frac{s_j}{s_j + s_k} \sum_{m \neq j,k} s_m \sigma^A_{km} \tag{18}$$

4 Data

The information used in this work was taken from SABI [2] data base, which collects annual balance sheet records from official registers. The initial sample includes data on food and beverage companies for the period 1993 – 2002, coded following the CNAE-93 Spanish classification system . The dependent variable y_{it} is defined as the output sales (for firm i and year t) deflated by the consumer price index. Labour, capital and materials are the three inputs considered for analysis. Labour (n) is measured by the number of employees, capital (k) by the book value of fixed assets less accumulated amortization deflated by an index of durable industrial goods, and materials (m) by material purchases also converted into constant values using the consumer price index.

Several filters were applied to the original sample of 6543 firms: those with less than six consecutive years on the selected variables were eliminated and also those firms with annual rise of the level of employment or fixed asset greater than 200%. This produced a final unbalanced panel of 13552 observations corresponding to 1837 firms, from which 565 have information on 6 consecutive years, 553 on 7, 413 on 8, 73 on 9 and 233 on 10. With regard to the kind of activity it is possible to distinguish 9 subsectors:

- 409 firms in ”151 meat industry” (Meat, hereafter),
- 80 in ”152 preserved fish” (Fish),
- 129 in ”153 preserved fruits and vegetables” (Fruits),
- 73 in ”154 organic oils and fats” (Oils),
- 78 in ”155 dairy industry” (Dairy),
- 70 in ”156 grain mill industry” (Grain),
- 126 in ”157 animal feeds” (Animal),
- 626 in ”158 other industries”, which encompasses bread, biscuits, puddings, sugar, chocolate, pasta, coffee, tea, spices, sauces, baby foods, etc., (Miscellaneous) and

[2] http://www.informa.es

Table 1: Mean values and coefficients of variation (in parentheses) for output, labour, capital and materials

	Meat	Fish	Fruits	Oils	Dairy	Grain	Animal	Mis	Drink
y	9452	13533	7833	17265	37656	7055	14321	8646	11756
	(2.90)	(1.66)	(1.82)	(3.45)	(2.47)	(1.38)	(2.95)	(5.17)	(3.11)
n	49	97	61	39	149	33	35	67	50
	(2.77)	(1.40)	(1.36)	(2.23)	(2.54)	(1.93)	(1.97)	(3.98)	(2.64)
k	2118	3165	2974	4734	10900	1670	3213	3517	7629
	(6.63)	(2.05)	(3.06)	(3.90)	(2.85)	(1.94)	(3.91)	(6.40)	(4.54)
m	7175	9101	4967	14448	24856	5008	11755	4674	5764
	(2.69)	(1.68)	(1.78)	(3.73)	(2.23)	(1.31)	(3.10)	(4.85)	(3.27)

Mean values are expressed in $10^3\epsilon$ except for labour which refers to number of employees

- 246 in "159 drink industry" (Drink).

Table 1 presents the sample means of the variables for each industry, together with the coefficients of variation. On average, the largest firms of the Spanish food industry appear in the Dairy industry, which has the highest mean values for all variables; the ranking by the output variable is followed by Oils, Animal, Fish and Drink industries. It is worth to note that micro companies were not eliminated and, for example, the minimum value for labour variable is one employee in all industries. This leads to a huge degree of heterogeneity among firms within each industry as the coefficients of variation show. In spite of this fact, the regression analysis assumes companies use a similar technology. Miscellaneous is, by far, the sector with more variability, followed by Drink, Meat, Animal and Oils.

5 Results

5.1 *Estimation*

Equation (2) can be estimated by different procedures, depending on the assumptions. Fixed and random effects models have been widely used, but a less restrictive estimation is possible by means of instrumental variables and the generalized method of moments (GMM). It is a more robust alternative that allows to cope with potential heteroskedasticity and autocorrelation of the error term and also endogeneity of the regressors. Given the difficulty in obtaining other variables correlated with the original ones but not with the error term, it arises the possibility of using these same variables but lagged as instruments. Time effects are modeled through dummy variables and firm effects, provided their large number, are eliminated by estimating the equation (2) in first differences:

$$\Delta \ln y_{it} = \sum_j \beta_j \Delta \ln x_{jit} + \frac{1}{2} \sum_j \sum_k \beta_{jk} \Delta \ln x_{jit} \ln x_{kit} + \Delta\lambda_t + \Delta\nu_{it} \tag{19}$$

Arellano and Bond (1991) propose the utilization of GMM and the orthogonality conditions between $\Delta\nu_{it}$ and the whole set of values $\ln y_{i1}, \ldots, \ln y_{iT}$, $\ln x_{1i1}, \ldots, \ln x_{1iT}$, $\ln x_{2i1}, \ldots, \ln x_{2iT}$,

..., $\ln x_{Ji1}, \ldots, \ln x_{JiT}$, considering an assumption of strong exogeneity of the regressors. The estimation by GMM is carried out in two stages, using the second a weighted matrix constructed with the residuals obtained in the first stage. The procedure followed in this work consists in regressing jointly the system of equations in first differences (19) and levels (2). It was proposed (by Arellano and Bover, 1995; Blundell and Bond, 1998, among other) in order to reduce the weakness of instruments, which is very common in production functions (see Blundell and Bond, 2000).

It is necessary to test lack of second order autocorrelation because the GMM estimator is based on $E(\Delta\nu_{it}\Delta\nu_{i,t-2}) = 0$. In addition, a Sargan test of overidentifying is used to validate the orthogonality restrictions.

DPD package for Ox (Doornik et al., 2002) was used for robust GMM estimations. Table 2 presents the second-step GMM translog coefficients for the nine industries considered and their robust standard errors in parentheses. Table 2 also contains some specification tests (p-values in parentheses) at the bottom.

The Wald statistics are distributed as χ^2 with 9 degrees of freedom under the null of lack of joint significance of the regressors, excluded time dummies. The hypothesis is clearly rejected for all industries. Wald statistics for time dummies are not provided but joint insignificance is always rejected.

The statistics for the null of no second-order serial correlation are asymptotically distributed as $N(0,1)$. All AR(2) p-values are greater or equal than 5 per cent and second-order autocorrelation does not seem to be a serious problem.

The Sargan statistics contrast the null of not overidentifying of the instruments, and are distributed as a chi-square with degrees of freedom equal to the number of instruments minus regressors (in these cases χ^2_{383}). The hypothesis of strong exogeneity (for each year all values of the variables are employed as instruments) is only rejected for Miscellaneous, so the sets of the instrumental variables are correctly used in 8 of 9 regressions. This rejection, for Miscellaneous, of instrumental variables is guessed to be due to the heterogeneity of the production process within this industry because when a deeper disaggregate level is chosen, the regressions over more homogeneous data validate the instruments. And in the same way, the regression for the overall Spanish food industry reject the use of the instruments.

Models with weaker exogeneity conditions, i.e. only past values of the variables as instruments for the equation in first difference, were estimated, but those of the strongest assumption are preferred taking into account the sequence of Sargan tests.

Output elasticities to input changes are calculated through the expression (3), which in matrix form for a three factor production function would be:

$$\epsilon_{it} = R_{it}\beta \tag{20}$$

where

$$R_{it} = \begin{pmatrix} 1 & 0 & 0 & \ln n_{it} & 0 & 0 & \ln k_{it} & \ln m_{it} & 0 \\ 0 & 1 & 0 & 0 & \ln k_{it} & 0 & \ln n_{it} & 0 & \ln m_{it} \\ 0 & 0 & 1 & 0 & 0 & \ln m_{it} & 0 & \ln n_{it} & \ln k_{it} \end{pmatrix} \tag{21}$$

and $\epsilon_{it} = \begin{pmatrix} \epsilon_{nit} & \epsilon_{kit} & \epsilon_{mit} \end{pmatrix}'$, $\beta = \begin{pmatrix} \beta_n & \beta_k & \beta_m & \beta_{nn} & \beta_{kk} & \beta_{mm} & \beta_{nk} & \beta_{nm} & \beta_{km} \end{pmatrix}'$. The covariance matrix of these elasticities could be obtain using R_{it} and the covariance matrix of

Table 2: Translog production functions and specification tests (second-step GMM estimation)

	Meat	Fish	Fruits	Oils	Dairy	Grain	Animal	Mis	Drink
β_n	0.75	0.65	0.21	1.09	0.44	0.37	0.48	0.30	0.83
	(0.13)	(0.15)	(0.19)	(0.37)	(0.17)	(0.20)	(0.29)	(0.13)	(0.17)
β_k	0.30	0.16	-0.11	0.03	0.30	0.12	0.17	0.20	0.14
	(0.07)	(0.14)	(0.12)	(0.15)	(0.16)	(0.16)	(0.15)	(0.10)	(0.12)
β_m	-0.01	0.17	0.40	-0.07	0.27	0.38	0.14	-0.27	-0.29
	(0.25)	(0.11)	(0.28)	(0.25)	(0.17)	(0.22)	(0.34)	(0.10)	(0.12)
β_{nn}	0.19	0.12	-0.02	0.15	0.07	0.05	-0.01	-0.05	0.22
	(0.04)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)	(0.02)	(0.07)
β_{kk}	0.03	0.02	0.03	0.03	-0.04	0.01	-0.01	0.06	0.04
	(0.02)	(0.03)	(0.02)	(0.05)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)
β_{mm}	0.23	0.18	0.07	0.19	0.12	0.11	0.16	0.23	0.25
	(0.04)	(0.02)	(0.05)	(0.04)	(0.03)	(0.04)	(0.05)	(0.03)	(0.03)
β_{nk}	0.03	0.02	0.01	0.00	0.05	0.04	0.09	0.03	0.00
	(0.03)	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
β_{nm}	-0.18	-0.14	-0.01	-0.18	-0.11	-0.08	-0.11	-0.03	-0.17
	(0.02)	(0.05)	(0.03)	(0.05)	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)
β_{km}	-0.07	-0.05	-0.01	-0.02	-0.01	-0.03	-0.04	-0.08	-0.05
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Wald (joint)	8914	1874	3919	7730	3126	3194	1703	4290	2500
p	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AR(2)	-0.54	-0.47	-1.58	-0.45	0.42	-1.12	-0.46	-1.57	-1.97
p	(0.59)	(0.64)	(0.11)	(0.65)	(0.68)	(0.26)	(0.65)	(0.12)	(0.05)
Sargan	344.30	54.27	106.82	51.00	55.37	53.37	102.87	478.02	233.49
p	(0.92)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(0.00)	(1.00)

Robust standard deviations for coefficients and p-values for tests are given in parentheses.

Table 3: Output elasticities to input changes, evaluated at mean log values

	Meat	Fish	Fruits	Oils	Dairy	Grain	Animal	Drinks
ϵ_n	0.13	0.16	0.10	0.10	0.13	0.11	0.09	0.22
	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)	(0.03)	(0.03)
ϵ_k	0.06	0.03	0.04	0.04	0.07	0.05	0.05	0.08
	(0.01)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
ϵ_m	0.80	0.73	0.81	0.86	0.77	0.79	0.88	0.67
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)

Robust standard deviations are shown in parentheses.

Table 4: Monotonicity (proportion of output elasticities greater than zero) and convexity

	Meat	Fish	Fruits	Oils	Dairy	Grain	Animal	Drinks
$\epsilon_n > 0$	0.806	0.897	1.000	0.699	0.920	0.946	0.804	0.882
$\epsilon_k > 0$	0.817	0.802	0.821	0.896	0.952	0.931	0.836	0.932
$\epsilon_m > 0$	0.994	0.990	1.000	1.000	1.000	1.000	1.000	0.987
convexity	0.015	0.202	0.603	0.157	0.590	0.419	0.272	0.089

the translog coefficents (Σ):

$$V\epsilon_{it} = R_{it}\Sigma R'_{it}$$

The average values of these elasticities are reported in Table 3. They are statistically significant and reasonable from an economic point of view. So labour elasticities are ranged from 0.09 (Animal) to 0.22 (Drink), capital elasticities from 0.03 (Fish) to 0.08 (Drink), and materials from 0.67 (Drink) to 0.88 (Animal). These variations are explained by the different technologies these industries use and indicate that a regression for the whole set would have not been appropriate. One regression for each industry offers the possibility of distinguishing between industries with the highest response to changes in labour input (and the least sensitive to material variations) such as Drink and Fish, or the most sensitive to material changes (and the least responsive to labour) such as Animal, Oils and Fruits. As regards capital input, the most sensitive are Drink, Dairy and Meat, and the least are Fish, Oils and Fruits.

These same elasticities are estimated for 12 Italian industries using a panel of 1272 firms in a recent work (Bottasso and Sembenelli, 2004) and are commented for comparison. Output elasticities with respect to materials take similar values as they vary between 0.66 and 0.84. But somewhat wider ranges are found for labour (from 0.10 to 0.37) and capital (between 0.03 and 0.12), probably due to a major difference in technology between Italian firms, with industries such as metals, minerals, chemical products, textile, etc. Italian food and drink industry takes an average output elasticity of 0.10 for labour, 0.06 for capital and 0.84 for materials in accordance with this work.

5.2 *Testing properties*

Output elasticities are also calculated for each sample value, and the proportion of them with input-output elasticities greater than zero (positive monotonicity) are shown in Table 4. The major part of the estimated elasticities in each point are positive and the data comply very well with the monotonicity condition. On average 92.04% of the input-output elasticities are positive (89.77% for ϵ_n, 86.80% ϵ_k and 99.56% ϵ_m).

However the results for convexity are not satisfactory, and only two industries, Fruits and Dairy, obtain satisfactory proportions. Perhaps this is the drawback of using the translog function: as a local approximation it seems difficult it satisfies convexity throughout a large domain of observations. This implies that global conclusions should not be drawn and only local interpretations are appropriate (Chambers, 1988).

Wald tests for restrictions on parameters (Greene, 2003) are reported in Table 5. The

Table 5: Wald tests for restrictions on parameters: homogeneity, constant returns to scale (CRS) and complete and pairwise strong and weak separability

		Meat	Fish	Fruits	Oils	Dairy	Grain	Animal	Drinks
Homogeneity		5.13	0.13	9.04	0.83	0.11	0.69	2.89	4.97
		(0.16)	(0.99)	(0.03)	(0.84)	(0.99)	(0.87)	(0.41)	(0.17)
CRS		8.97	8.01	12.03	1.02	1.20	3.05	3.70	7.86
		(0.06)	(0.09)	(0.02)	(0.91)	(0.88)	(0.55)	(0.45)	(0.10)
Complete		128.86	295.92	10.87	77.41	16.82	39.62	23.35	96.84
		(0.00)	(0.00)	(0.09)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Strong	n,k	107.85	23.98	0.71	58.19	15.19	23.99	8.22	39.23
		(0.00)	(0.00)	(0.70)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
	n,m	29.39	5.20	0.43	0.99	3.42	3.67	15.14	5.13
		(0.00)	(0.07)	(0.81)	(0.61)	(0.18)	(0.16)	(0.00)	(0.08)
	k,m	57.72	10.81	0.44	10.88	10.31	12.51	11.98	25.54
		(0.00)	(0.00)	(0.80)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Weak	n,k	2.29	0.32	0.93	0.37	2.22	0.19	2.70	2.83
		(0.32)	(0.85)	(0.63)	(0.83)	(0.33)	(0.91)	(0.26)	(0.24)
	n,m	30.07	6.78	0.47	2.71	2.95	6.59	5.89	6.92
		(0.00)	(0.03)	(0.79)	(0.26)	(0.23)	(0.04)	(0.05)	(0.03)
	k,m	37.67	7.07	2.65	0.94	5.32	6.88	1.79	7.17
		(0.00)	(0.03)	(0.27)	(0.62)	(0.07)	(0.03)	(0.41)	(0.03)

p-values in parentheses.

Table 6: Number of scale elasticities lower and higher than unity at 5% level using a normal distribution

		Meat	Fish	Fruits	Oils	Dairy	Grain	Animal	Drink
$E_{it} < 1$	GMM	263	221	466	0	0	7	0	568
	OLS	3002	455	860	152	443	523	434	1791
$E_{it} > 1$	GMM	0	0	54	0	0	0	24	47
	OLS	0	0	0	0	0	0	0	0
Observations		3017	585	988	509	566	540	941	1791

$E_{it} < 1 \rightarrow \frac{E_{it}-1}{\sqrt{VE_{it}}} < -1.6449$; $E_{it} > 1 \rightarrow \frac{E_{it}-1}{\sqrt{VE_{it}}} > 1.6449$.

homogeneity hypotheses are not rejected at 1% level, and only Fruits offers a small critical value (0.0288). The point is that, for these industries, one cannot reject the curvatures of isoquants are independent of the size of the firm, and thus the relative usages of factors and their substitution relationships are solely related to relative factor prices and not to output levels.

In a similar way, constant returns to scale are not rejected at 1% level for any industry although Fruits gives a rather small p-value (0.0171). Since the elasticity of scale is the sum of the output elasticities and these can be interpreted as the ratio between marginal productivity and average productivity, the fact that scale elasticity is not rejected to be equal to one means that the technologies analysed are placed at stage II of the production process. That is, they have downward sloped average productivities that are higher than marginal productivies. This can indicate that there are not too much room to increase the size of the firms. Furthermore, by duality, the elasticity of scale is always equal to the elasticity of size in homothetic production functions (Chambers, 1988, page 73). Therefore, constant returns lead to not reject that the firms are in the minimum of the average cost curve without incentives neither to increase nor to decrease.

OLS estimates have not included but they do not lead to the same conclusions: homogeneity is rejected for Meat, Dairy, Animal and Drink, whereas constant returns are reject for all industries except for Oils.

Given convexity is not satisfactory, it seems advisable to study the behaviour of constant returns to scale throughout the domain. The elasticity of scale at each point (E_{it}), and its variance (VE_{it}), can be computed using (20), (21) and the unity vector $i = \begin{pmatrix} 1 & 1 & 1 \end{pmatrix}$ (Dios, 2003):

$$E_{it} = i\,\epsilon_{it}$$

$$VE_{it} = i\,R_{it}\,\Sigma\,R'_{it}\,i'$$

Table 6 provides the number of observations with scale elasticities statistically lower and higher than unity at 5% significance level. Industries in Table 5 with high probabilities for not rejecting constant returns, such as Oils, Dairy, Grain and Animal present none or few elasticities of scales not equal to one when GMM estimator is used. The other four industries gives many observations for which decreasing returns to scales is an acceptable hipothesis. The proportion of them for Meat is not too important, 8.7%. But it is for Drink 31.7%, Fish 37.8% and Fruits 47.2%. Note that the conclusion had been very different by using OLS because the bulk of observations, whatever the industry, shows decreasing returns. On the other hand, increasing returns to scales are only observed in three industries and not with much relevance: Animal (2.5%), Drink (2.6%) and Fruits (5.5%).

Complete separability is sound rejected for all industries apart from Fruits, and this means that for this industry strong and weak separability are found for all groups of inputs as can be seen in Table 5. The production technology can be described by the Cobb-Douglas specification only in the Fruits industry. In the remaining 7 industries strong separability n, k from m and k, m from n are rejected, whereas strong separability n, m from k is not rejected in Oils, Dairy, Grain, and more marginally in Drink and Fish. However the three weak separability conditions are jointly satisfied in Fruits, Oils, Dairy and Animal and more marginally in Fish, Grain and Drinks. Meat firms only fulfilled n, k from m weak separability.

Table 7: Morishima and Shadow elasticities of substitution at mean log values

	Meat	Fish	Fruits	Oils	Dairy	Grain	Animal	Drink
Morishima								
σ^M_{nk}	2.28	0.95	2.97	3.03	-0.06	-2.72	0.19	2.58
σ^M_{kn}	0.80	5.19	0.28	-0.26	3.17	7.70	0.71	-1.27
σ^M_{nm}	-1.55	-2.40	1.40	-1.64	7.89	-42.59	-3.32	-4.72
σ^M_{mn}	-0.88	-1.08	0.97	-1.35	6.44	-27.63	-1.74	-4.14
σ^M_{km}	-0.06	-6.65	4.09	1.64	4.66	-53.01	-3.83	-0.87
σ^M_{mk}	1.62	-0.38	3.40	2.73	1.39	-17.69	-1.38	2.00
Shadow								
σ^S_{nk}	1.81	1.61	2.16	2.05	1.06	0.29	0.39	1.55
σ^S_{nm}	-0.98	-1.31	1.02	-1.38	6.65	-29.51	-1.88	-4.28
σ^S_{km}	1.50	-0.62	3.43	2.68	1.66	-19.65	-1.52	1.69

However, these results on separability should not be took as a definite conclusion because translog function impose a rather inflexible structure of the coefficients to hold separability and thus it is not a good way to treat this issue (Chambers, 1988).

5.3 ***Substitution elasticities***

Substitutability and complementarity between production factors in response to price changes are studied through Morishima and Shadow elasticities of substitution, whose estimates at mean log values are shown in Table 7.

Labour and capital are always substitutes ($\sigma^S_{nk} > 0$), indicating that an increase in relative price of one factor, say labour ($\Delta \frac{P_n}{P_k}$) , would produce an increase in the relative use of capital ($\Delta \frac{x_k}{x_n}$). The most sensitive industries seem to be Fruits ($\sigma^S_{nk} = 2.16$) and Oils (2.05) and the least Grain (0.29) and Animal (0.39). The Morishima elasticities show the response to changes in wages and capital prices is not homogeneous, and some industries present labour and capital as Morishima complements ($\sigma^M_{nk} < 0$ or $\sigma^M_{kn} < 0$) although the compensated effect of Shadow elasticities is always positive.

Labour and materials are complements (Morishima and Shadow) in six industries, with Fruits and Dairy being the exception. This complementarity relationship means, for instance, that a rise of relative material price would induce a decrease in the absolute and relative quantity of labour ($\sigma^M_{nm} < 0$, $\sigma^S_{nm} < 0$). Extremely high values are obtained for the Grain industry. Looking at Morishima elasticities, firms appear to be more sensitive to changes in material prices than to labour prices since $|\sigma^M_{nm}| > |\sigma^M_{mn}|$ is always found.

Major heterogeneity can be seen in capital and materials relationships. Five industries, Meat, Fruits, Oils, Dairy and Drink, classify them as substitutes, and three, Fish, Grain and Animal, as complements.

Table 8 gives information on how many positive elasticities are found throughout the domain. It confirms the results mentioned above. Labour and capital, as well capital and materials, are mainly p-substitutes For the labour-capital pair, on average 81.44% of σ^S_{nk} are positive,

Table 8: Proportion of Shadow elasticities of substitution greater than zero

	Meat	Fish	Fruits	Oils	Dairy	Grain	Animal	Drink
$\sigma^S_{nk} > 0$	0.86	0.85	0.78	0.71	0.80	0.95	0.74	0.77
$\sigma^S_{nm} > 0$	0.26	0.57	0.99	0.52	0.67	0.53	0.52	0.24
$\sigma^S_{km} > 0$	0.67	0.61	0.78	0.74	0.83	0.57	0.52	0.56

whereas for capital-materials the figure is 64.84%. With regards to labour-material, they are p-complements for Meat and Drink industries, as the bulk of elasticities are negative, and p-substitutes for Fruits. But the remaining industries present similar quantities of positive and negative elasticities.

6 Conclusions

The production structure of the Spanish food industry is analyzed at firm level using 9 panel data sets and by means of (i) estimating three-factor translog production functions with a robust procedure to heteroskedasticity, autocorrelation and endogeneity bias, (ii) testing restrictions on parameters and (iii) estimating elasticities of substitution.

Only one out of nine regressions is not appropriate with the GMM procedure. The reason seems to be the heterogeneity of the production process within Miscellaneous classification.

The Spanish food data used in this work do not seem to have problems of positive monotonicity, as the 92% of the computed output elasticities to input changes are positive. But convexity is not satisfactory and this leads to not take global conclusions and examine the behaviour of the function at each point.

Neither homogeneity nor constant returns to scale are rejected at 1% level in the 8 industries. But a more detailed analysis shows that only for Oils, Dairy, Grain and Animal industries the hypotheses of constant returns are accepted throughout their domains; Meat industry presents a relatively low rate of observations with decreasing returns; but the remaining industries, Drink, Fish and Fruits, offer high proportions of firms for which decreasing returns to scale are not rejected.

A major precaution is recommended for the separability between inputs because, besides the convexity problem, the translog function is considered very inflexible to study these issues. Even so, complete separability is overwhelmingly rejected for 7 industries and all seems to indicate that the Cobb-Douglas function would not be appropriate to represent their technologies. Only for Fruits it would be correct.

The response of output to input changes is not the same in each industry because of their different production process. And output elasticities allow to classify them on their degree of variation to changes in each input. In this way the industries with the highest sensitivity to changes in labour input are Drink and Fish, the most sensitive to material changes are Animal, Oils and Fruits, and the most sensitive to capital are Drink, Dairy and Meat.

The relations between pairs of inputs show that labour and capital, and capital and materials, are p-substitutes for all industries. There is not evidence that the same conclusion would be appropriate for labour and materials, being the opposite plausible in Meat and Drink industries.

Finally, a comment on the estimation procedure. The generalised method of moments, as mentioned above, is robust to heteroskedasticity and autocorrelation and copes with the endogeneity of regressors, but from the point of view of the obtained results, the conclusion is that it allows to not reject several hypotheses, such as constant returns, which had been rejected using ordinary least squares.

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