EXPORTING AND PRODUCTIVITY: FIRM-LEVEL EVIDENCE FOR SPANISH MANUFACTURING

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Abstract:

This paper measures total factor productivity differences between exporters and non-exporters on the basis of an unbalanced panel of Spanish manufacturing firms over the period 1990-1999. To compute these differences we estimate production functions following the GMM approach proposed by Blundell and Bond (1999). After controlling for unobserved heterogeneity and simultaneity bias produced by the effect of productivity of the firm itself on output decisions, the results we obtain indicate higher levels of productivity for exporters than for non-exporters: in three out of the four estimated industries we find that export-oriented firms are more productive than domestic firms.

1. Introduction

One of the factors that are thought to be important to make some firms more productive than others is exporting. Bartelsman and Doms (2000) survey of the literature on productivity that uses longitudinal micro-level data sets points out to the link between productivity and exporting as one of the factors this literature has focused on (the rest of factors are regulation, management/ownership, technology and human capital). Studies by Aw and Hwang (1995) on Taiwan; Bernard and Jensen (1995) (1999) on the US; Bernard and Wanger (1997) on Germany; Clerides, Lach and Tybout (1998) on Colombia, Mexico and Marocco; Aw, Chung and Roberts (2000) on Taiwan and South Korea; Girma, Greenaway and Kneller (2002) on the UK, provide evidence on the fact that export-oriented firms are more productive than non-exporters.

Sunk costs are the main argument outlined to explain why exporters are more efficient than non-exporters, in particular the existence of higher sunk entry costs for exporters with respect to non-exporters. The argument comes from models of industry dynamics –Jovanovic (1982) and Hopenhayn (1992)- and applies also to entry and exit to export markets as suggested by Aw, Chen and Roberts (1997). According to this argument, differences in sunk entry costs can explain productivity differences between exporters and domestic-oriented firms. Building on these ideas Roberts and Tybout (1997), Clerides , Lach and Tybout (1998) and Bernard and Jensen (2001) have developed models of the decision to export. The result that firm's previous export status is a determinant of the decision to export is interpreted, in term of these models, as a favorable evidence to the existence of sunk entry cost in the export market.

In a previous paper, Delgado, Fariñas and Ruano (2002), we measure total factor productivity differences between exporters and non-exporters on the basis of a sample of Spanish manufacturing firms. The empirical analysis confirm higher levels of productivity for exporting firms relative to non-exporting firms. With respect to the relative merits of the selection and the learning hypotheses proposed to explain the greater productivity of exporters, we find evidence favorable to the self-selection of more productive firms into the export market. It is much harder to find evidence in favor of learning effects in the data set. For the whole sample of manufacturing firms we do not find any systematic evidence consistent to learning-by-exporting. However, restricting the sample to the group of younger firms we observe that post-entry productivity growth is greater for young entering exporters than for young entering domestic firms and with no contact to the export market. With the exception of the latter result, our empirical findings are very much in line with those reported in the literature -Bernard and Jensen (1999).

The purpose of this paper is to investigate further total factor productivity differences between exporters and non-exporters, measuring these productivity differences by the estimation of production functions. Productivity shocks are assumed to be an unobserved firm-specific effect that can be recovered as the difference between actual and predicted output and that are allowed to take a very general form. We identify two advantages from using this approach. The first one refers to the set of assumptions that is required to get unbiased estimates of total factor productivity when using index numbers. Some of them, as the assumption of constant returns to scale, may be relevant for measuring correctly productivity differences between exporters and non exporters. The estimation of production functions allows to relax some of these assumptions. The second advantage refers to the benefits that can be derived from the application of GMM estimators that we use. In particular, these estimators permit to control two likely sources of bias in the OLS results: 1) the elimination of unobserved firm heterogeneity that is time invariant and 2) the use of lagged instruments to correct for simultaneity bias produced by the effect of productivity of the firm itself on the input decisions. The paper estimates productivity differences for exporters and non-exporters using an unbalanced panel of Spanish manufacturing firms over the period 1990-1999. We apply estimators developed in Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998). An illustration of these procedures in the context of the estimation of production functions can be found in Blundell and Bond (1999) and Bond (2002). Griffith (1999) contains a similar application to the analysis of productivity differences between foreign and domestic owned establishments.

The rest of the paper is organized as follows. Section 2 describes some characteristics of the data set used in the analysis and presents some basic evidence on the magnitude of performance differences between exporters and non-exporters. Section 3 discusses the method used and presents the econometric estimates of production functions in four industries –textiles and clothing; manufactures of metal products; food industry and timber, wooden products and furniture. Conclusions are placed in section 4.

2. The premium to exporting

This section contains two parts. In the first part we begin by describing the characteristics of the data set used in the analysis. In the second part we provide some basic descriptive evidence on the magnitude of performance differences between exporters and non-exporters.

2.1 Database characteristics

The data that we use come from a longitudinal data set of Spanish manufacturing firms. The survey for this data set is the *Encuesta sobre Estrategias Empresariales* (ESEE) directed and supported by the *Fundación Empresa Pública* and the Spanish Ministry of Industry. The information is available over the period 1990-1999.

One of the characteristic of this data set is that it is representative of manufacturing firms in the Spanish economy. The sample covers the population of Spanish manufacturing firms with 200 or more employees. Firms with at least 10 employees but less than 200 employees were selected by a random sampling scheme in the initial year. In subsequent years firms that drop out of the original sample are replaced every year by newly created firms, according to the sampling procedure that was used in the base year. Therefore, the data set reproduces the process of entry and exit that takes palace in the population. The data set consists of 2,188 firms in 1990. Due to entry and exit, the resulting data set is an unbalanced panel of 3,151 manufacturing firms over the period 1990-1999 (for further technical details on the data set see Fariñas and Jaumandreu, 1999).

The estimation process presented in section 3 restricts the sample of firms. On one hand, we require complete information on output, labor input, material , capital stock and exports for each firm. On the other hand, we further restrict the sample to those firms that report a complete sequence of information of at least four or more consecutive years over the period 1990-1999. Both restrictions resulted in a usable sample of 1,403 firms, yielding a total number of 10,469 observations.

Table 1 provides summary statistics for the group of exporting firms and non-exporting firms. Each observation has been classified according to their current export status. According to this classification of exporters, 56% of the sample corresponds to exporters and the rest to non-exporters. This proportion of exporters is similar to the percentage of firms reporting that they are exporters in the ESEE for the whole sample of firms.

On average exporters are larger than non-exporters, employing 273.2 and 54.3 respectively. When size is measured by the value of production the relationship between size and exporting is also evident, with a value of 10,230 for exporters and 1,287 for non-exporters in €000s. On average the labor productivity of exporters is 69% higher relative to non-exporters. Exporting firms have also higher labor costs than non-exporters. Therefore, summary statistics suggests the existence of a strong performance gap between exporters and non-exporters for a variety of firms characteristics.

2.2 **Estimates of export premia**

To estimate the difference between exporters and non-exporters more precisely, we calculate the export premia after controlling for industry and size characteristics. As in the tradition initiated by Bernard and Jensen (1995), export premia are estimated from a regression of the form:

$$\ln X_{it} = \alpha + \beta \, \text{Export}_i + \sum_s \lambda_s \text{size}_{it} + \sum_I \gamma_I \text{Industry}_i + \sum_T \delta_T \text{Year}_t + \varepsilon_{it} \qquad (1)$$

where X_{it} is some characteristic of firm i at time t; $Export_t$ is a dummy variable for current export status; $Size_{it}$ is a set of size dummies that assign a size category in terms of number of workers to each firm i at time t; $Industry_i$ is a set of NACE-CLIO (R-44) industry dummies; $Year_t$ is a collection of year dummies and ε_{it} is a random error. The omitted categories are smaller firms, Ferrous and non-ferrous metals industry and the year 1990.

Results from specification (1) are given in Table 2. After controlling for industry, size and year effects, the sign of the estimated coefficient β indicates that exporting is positively and significantly correlated with various measures of business performance. The largest difference is found in the size of exporters. Exporters are larger than non-exporters. Taking the value of production as a measure of size, exporters have an average size approximately three times the size of non-exporters. A similar pattern has been found in data sets referred to different countries (see Bernard and Jensen, 1999; Bernard and Wanger, 1997; Girma, Greenaway and Kneller, 2002). Measures of labor productivity are also significantly higher for exporters. We find that production per hour of work is 45% higher for exporters and the difference is 27% if productivity is measured in terms of value-added per hour. A part of these differences is the result of a higher capital intensity, as exporters use a stock of capital per unit of labor 48% higher than non-exporters.

Export premia are also present in other labor market indicators. Workers in exporting firms benefit from higher wages. On average, wages are 14% higher for exporters relative to non-exporters. The mean wage differential is smaller than the mean productivity difference between exporters and non-exporters.

3. Estimating productivity differences between exporters and non-exporters

The use of index numbers to measuring total factor productivity is widespread. Either bilateral or multilateral indexes have been defined to perform comparisons among groups of firms (Caves, Christensen and Diewert, 1982; and for a review article Good, Nadiri and

Sickles, 1996). In the case of productivity comparisons between exporters and non-exporters, the index number approach has been applied by Aw, Chen and Roberts (1997); Aw, Chung and Roberts (2000); Delgado, Fariñas and Ruano (2002). The use of index numbers requires the imposition of a set of assumptions to get unbiased measures of total factor productivity. These assumptions include constant returns to scale, perfect competition in the output market and instantaneous input adjustment.

An alternative approach to measuring total factor productivity is the estimation of production functions. This approach allows relaxing part of the assumptions associated with the use of index numbers. In the following section we define the approach based on the estimation of production functions that permits to test the differences between exporters and non-exporters.

3.1 Methodology

Our purpose is to measure TFP level differences between exporters and non-exporters. To investigate the magnitude of these differences, we consider the estimation of a production function with productivity shocks that are allowed to take a very general form. The estimation is performed using a large panel of manufacturing firms. We follow the estimation method proposed by Blundell and Bond (1999). Next, we briefly summarize the approach.

Consider that firm i produce at time t according to a Cobb-Douglas production function that in linear form can be expressed as:

$$y_{it} = \alpha l_{it} + \beta m_{it} + \gamma k_{it} + a_{it}$$

where y_{it} is log of output, l_{it} is log of labor input, m_{it} is log of intermediate inputs, α, β and γ are the elasticities of the output with respect to labor, intermediate inputs and capital respectively. If $\alpha + \beta + \gamma = 1$ the production technology presents constant return to scale.

The term a_{it} can be interpreted as the level of TFP and can be decomposed in three components:

$$a_{it} = h_i + h_t + u_{it}$$

where h_i is an individual effect that captures firm-specific differences in productivity, h_t captures macroeconomic shocks in productivity which are fixed over firms, and u_{it} picks up firm-specific productivity shocks that we could assume to be idiosyncratic. This static representation of the production function can be estimated or, alternatively, we can think that u_{it} is probably persistent over time as a consequence of factors such as omitted variables, adjustment costs, etc. Consider that disturbances u_{it} adopt an autorregresive form,

$$u_{it} = r\, u_{it-1} + e_{it}$$

where e_{it} is an idiosyncratic error term. This assumption permits the following dynamic representation of the production function:

$$y_{it} = d_1 y_{it-1} + d_2 l_{it} + d_3 l_{it-1} + d_4 m_{it} + d_5 m_{it-1} + d_6 k_{it} + d_7 k_{it-1} + d_8 (h_i + h_t) + e_{it} \quad (2)$$

where the parameters to be estimated are:

$$d_1 = r,\ d_2 = a,\ d_3 = -ra,\ d_4 = b,\ d_5 = -rb,\ d_6 = g,\ d_7 = -rg,\ d_8 = 1 - r$$

This set of parameters imply three common factor restrictions ($d_3 = -d_2$; $d_5 = -d_4$; $d_7 = -d_6$), which can be tested and/or imposed for the estimation of the parameters (α, β, γ, ρ).

To test whether exporting firms have a higher level of total factor productivity than non-exporting firms we follow the approach proposed by Griffith (1999) to measure differences between foreign-owned and domestic-owned firms. Given that η_i captures firm specific differences in productivity that are fixed over time, it is possible to measure the mean of η_i across the two groups of firms we are interested in. Therefore, parameterizing the firms-specific component by a dummy variable equal to one for the group of exporters and zero otherwise we can test for the average difference of total factor productivity for exporters relative to non-exporters.

3.2. Definition of variables

Variables are defined as follows:

Output:

Measured by annual gross production of goods and services (sales plus the change in the stocks of work in progress and of goods on hand for sale) expressed in real terms using individual price indexes for each firm drawn from the ESEE.

Labor input:

Measured by the number of effective yearly hours of work, which is equal to normal yearly hours plus overtime yearly hours minus non-worked yearly hours picked up in the ESEE.

Materials:

Measured by the cost of intermediate inputs, which includes raw material purchases, energy and fuel costs and other costs paid for by the firms. This concept is expressed in real terms using individual price indexes of intermediate inputs for each firm drawn from the ESEE

Capital stock:

Replacement value of the net capital stock in equipment calculated following the perpetual inventory method:

$$k_t = I_t + k_{t-1}(1-d)\frac{P_t}{P_{t-1}}$$

where I_t represents investment in equipment and comes from the ESEE, d stands for depreciation rates from the Spanish Ministry of Industry, and P_t corresponds to price indexes for equipment published by Spanish Instituto de Estadística. Single average price adjustment were used to construct an initial value of net capital stock in equipment for each firm from the book values of equipment and the average age of them. Both concepts are provided in the ESEE.

Labor cost:

Measured by the sum of wages, social security contributions and other labor cost paid by the firms drawn from the ESEE.

3.3 Production function estimates

The issues of unobserved heterogeneity and potential simultaneity in the estimation of production functions of the form of (2) have been addressed using the GMM first-differenced estimator (Arellano and Bond, 1991). An statistical shortcoming with this approach has been recently suggested by Blundell and Bond (1999) who argue that when the explanatory variables are persistent over time, lagged levels of these variables are weak instruments for the regression equation in differences. Company variables from micro panel data sets such as sales, production, employment, capital, hours, etc. tend to present the statistical property of being highly persistent as documented in Blundell and Bond (1999) and Griffith (1999). Therefore, in the estimation of equations of the form (2) the instrument weakness has negative consequences on both the asymptotic efficiency and the small-sample bias of the difference estimator.

Arellano and Bover (1995) and Blundell and Bond (1998) have proposed an alternative system estimator that reduces the biases associated with the standard difference estimator. This estimator combines in a system the regression in differences with the regression in levels. The instruments for the regression in differences are the lagged levels of variables consistent with the moment conditions. For the other component of the system, the equation in levels, the instruments are given by the lagged differences of the variables. This latter part of the system requires additional moment conditions that are only valid under the assumption of no correlation between the variables in differences and the fixed effect, although there may be correlation between the right-hand side variables in levels and the firm specific effect. This assumption results from the stationary condition: $E\lfloor X_{i,t+p} \cdot \eta_i \rfloor = E\lfloor X_{i,t+q} \cdot \eta_i \rfloor$, for all p and q, where X is the set of explanatory variables in the moment conditions.

We present the results from the estimation of the dynamic Cobb-Douglas production function for four sectors: Textiles and clothing, Manufacture of metal products, Food industry and Timber, wooden products and furniture. The former three industries have been chosen because of the great number of available observations, more than 1,100 for each industry (see Table 3). Timber, wooden products and furniture industry, with a smaller number of observations (around 700), has been also selected. In the sample, this industry has shown during the period a continuos increase in the proportion of exporters, going from around 18% in 1990 to 50% in 1999. We have also examined another two industries, Chemical products and Motor vehicles, with a high percentage of exporters. Specification tests do not confirm the validity of the GMM estimators and results on both industries are not presented for the moment.

Tables 4-7 report the results from the estimation of equation (2) for the four selected industries using OLS, first-differenced and the system estimator. While there are a number of similarities among the various estimates, our preferred estimation method uses the GMM system estimator.

Table 4 presents the results of the textiles and clothing industry. A complete set of year dummies is included in all columns to control for common productivity shocks to all firms in the industry. The OLS estimates of column (1) indicate that exporters have, on average, higher total factor productivity levels than non-exporters. The OLS coefficients are biased if unobserved specific firm effects are correlated with the explanatory variables. Column (2) and (3) present first-difference GMM estimates and system GMM estimates, respectively. In column (2) levels of output, intermediate and labor inputs dated (t-2), (t-3) and (t-4) are used as instruments for the difference equation. Column (3), for the system estimator, uses the same level instruments as in column (2) plus differences of output, intermediate and labor input dated (t-1).

The consistency of the GMM estimators depends on whether lagged values of the explanatory variables are valid instruments in the production function equation. To address this issue four specification tests are reported (Arellano and Bond, 1998). The Sargan test fails to reject the validity of the instruments at the 5% level but it does at the 10% level. The second test is the Sargan-Differences test, which examines the null hypothesis that the lagged differences are uncorrelated with the residuals. Therefore, the Sargan-difference test does not reject the validity of the additional restrictions imposed in the system estimator. Even with uncorrelated original error term, first-order serial correlation of the differenced error is expected and confirmed by test statistics. Finally, the test fails to reject the null hypothesis of absence of second-order serial correlation. Overall, the reported specification tests indicate the validity of the moment conditions used in the system GMM.

Although the pattern of signs on current and lagged regressors in the estimations are consistent with the AR(1) error specification, the common factor restrictions test are rejected for the OLS estimator. It also rejects constant returns to scale. The comparison of coefficients from first-differenced and system equations is consistent with expectations of first-differenced coefficients to be biased downwards if the available instruments are weak (Blundell and Bond, 1999). The common factor restrictions and the constant returns to scale are easily accepted in the system GMM results.

All columns indicate a high degree of persistence, with a coefficient on the lagged dependent variable significant and equal to 0.49 with the system estimator.

The results in the system-GMM indicate that exporters have a permanently higher level of total factor productivity than non-exporters. The magnitude of the coefficient indicates that after conditioning on inputs, exporters have about 7.5% higher output than non-exporters.

Tables 5-7 report results on three additional sectors: manufacture of metal products; food industry; and timber, wooden products and furniture. We do not comment on the results for each sector separately but indicate some general patterns. The specification tests shown for the three industries indicate that the validity of instruments cannot be rejected. The pattern of signs on current and lagged regressors is consistent with the assumed error specification and the common factor restriction is not rejected at the 10%. The hypothesis of constant returns to scale cannot be rejected for two industries -metal products and food- with the system GMM estimates. However in timber, wooden products and furniture constant returns to scale is rejected. For the three industries, the coefficient of the lagged dependent variable is around 0.2-0.3 indicating a degree of persistence slightly lower than in the textile and clothing.

The coefficients estimating the average difference between exporters and non-exporters indicate that these differences are significant in the system-GMM in the three sectors. In two sectors -metal products and timber, wooden products and furniture- exporters have an output (conditional on inputs) that is 3.6 and 4.4 higher than non-exporters. In textiles and clothing the difference is unfavorable to exporters, with an output 15.7 % lower than non-exporters, after conditioning on inputs.

4. Summary

This paper measures total factor productivity differences between exporters and non-exporters. The estimation is based on an unbalanced panel of Spanish manufacturing firms over the period 1990-1999.

To compute these differences we consider the estimation of a Cobb-Douglas production function with productivity shocks that are allowed to take a very general form. The estimation follows the GMM approach proposed by Blundell and Bond (1999) especially suitable to deal with models for moderately persistent series from short panels.

After controlling for unobserved heterogeneity and simultaneity, the results we obtain indicate higher levels of productivity for exporters than for non-exporters: in three out of the four estimated industries we find that export-oriented firms are more productive than domestic firms.

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Table 1

Mean characteristics of firms: exporters vs. non-exporters

	Exporters	Non-exporters
Production (000 €)	10,230.2	1,287.1
Employment (number)	273.2	54.3
Labor productivity (000 € per employee)	117.9	69.5
Labor costs (000 € per employee)	22.7	16.6
Number of observations	5,874	4,595

Table 2

The premium to exporting for various firm characteristics

Dependent variable	Exporter dummy (t-statisitc)
Production (size)	1.92
	(26.3)
Labor productivity:	
Value-added per hour	0.27
	(8.5)
Production per hour	0.45
	(13.2)
Wage per hour	0.14
	(8.14)
Capital intensity	0.48
	(8.7)
Number of observations	10,469

Numbers are coefficients on a export dummy in a regression of the form (1) described in the text; numbers in parenthesis are t-statistics robust to heteroskedasticity.

Table 3
Percentage of exporters and number of observations by industry

Industry classification NACE-CLIO R44	Number of observations	% of exporters	
		1990	1999
1 Ferrous and non-ferrous metals	235	76.5	78.3
2 Non-metallic mineral products	758	41.8	52.1
3 Chemical products	733	67.7	77.8
4 Manufactures of metal products	1,108	46.0	57.9
5 Agricultural and industrial machinery	581	74.4	78.2
6 Office and data processing machines, etc.	74	100.0	71.4
7 Electrical goods	688	74.5	73.1
8 Motor vehicles	454	83.8	85.4
9 Other transport equipment	196	70.6	83.3
10 Meats, meat preparation and preserves	361	28.0	65.6
11 Food industry	1,190	31.2	41.0
12 Beverages	262	34.8	63.2
13 Textiles and clothing	1,224	48.9	59.5
14 Leathers, leather and skin goods, footwear	350	62.5	75.0
15 Timber, wooden products and forniture	696	17.9	50.0
16 Paper andd printing products	795	36.8	55.6
17 Rubber and plastic products	505	56.7	66.7
18 Other manufacturing products	259	82.6	85.7
Total manufacturing	10,469	51.4	62.8

Table 4
Textiles and clothing
Production function: alternative estimators
(dependent variable: output y_{it})

	(1) OLS	(2) Differences GMM	(3) System GMM
y_{it-1}	0.777	0.298	0.488
	(0.026)	(0.043)	(0.032)
l_{it}	0.387	0.474	0.570
	(0.043)	(0.092)	(0.058)
l_{it-1}	-0.298	-0.150	-0.330
	(0.041)	(0.072)	(0.048)
m_{it}	0.390	0.286	0.404
	(0.029)	(0.039)	(0.021)
m_{it-1}	-0.268	-0.122	-0.140
	(0.030)	(0.026)	(0.018)
k_{it}	0.067	0.030	0.035
	(0.018)	(0.016	(0.013)
k_{it-1}	-0.059	0.012	-0.021
	(0.016)	(0.015)	(0.010)
$Exporters_i$	0.049		0.075
	(0.016)		(0.020)
Instruments	-	t-2	t-2 and Δ(t-1)
Sargan (P-value)	-	0.078	0.083
Sargan-Difference (P-value)	-	-	0.333
m1 (P-value)	0.015	0.000	0.000
m2 (P-value)	0.143	0.371	0.371
Comfac (P-value)	0.025	0.434	0.493
CRS (P-value)	0.002	0.406	0.552
Number of observations	1058	892	1058
(number of firms)	166	166	166

Notes: All regressions are estimated in DPD (see Arellano and Bond, 1998); a set of year dummies is included in all models; numbers in parenthesis are two step robust standard errors; Sargan is the P-value from a test of over-identifying restrictions, which test the overall validity of instruments for the GMM estimators; Sargan-Difference is the P-value from a test of the validity of the additional restrictions imposed in the system estimator with respect to the difference estimator; m1 and m2 are the P-values from test of first and second order serial correlation; Comfac is the P-value from a test of the common factor restrictions; CRS is the P-value form a test of constant returns to scale; column (2) presents the results from a differences GMM estimator that uses as instruments $y_{it-2}...y_{it-4}$, $l_{it-2}..l_{it-4}$ and $m_{it-2}..m_{it-4}$; the results of column (3) are from a system GMM estimator with the same instruments as in column (2) plus instruments (y_{it-1}-y_{it-2}), (l_{it-1}-l_{it-2}) and (m_{it-1}-m_{it-2}) .

Table 5
Manufacture of metal products
Production function: alternative estimators
(dependent variable: output y_{it})

	(1) OLS	(2) Differences GMM	(3) System GMM
y_{it-1}	0.567	0.161	0.322
	(0.041)	(0.037)	(0.028)
l_{it}	0.415	0.355	0.666
	(0.057)	(0.074)	(0.041)
l_{it-1}	-0.309	-0.186	-0.321
	(0.057)	(0.048)	(0.036)
m_{it}	0.435	0.457	0.385
	(0.049)	(0.035)	(0.020)
m_{it-1}	-0.160	-0.119	-0.078
	(0.052)	(0.031)	(0.018)
k_{it}	0.036	0.002	0.031
	(0.016)	(0.019)	(0.014)
k_{it-1}	0.007	0.041	0.023
	(0.014)	(0.013)	(0.010)
$Exporters_i$	0.001		0.036
	(0.011)		(0.015)
Instruments	-	t-2	t-2 and Δ(t-1)
Sargan (P-value)	-	0.275	0.106
Sargan Difference (P-value)	-	-	0.079
m1 (P-value)	0.057	0.000	0.000
m2 (P-value)	0.805	0.960	0.677
Comfac (P-value)	0.000	0.002	0.105
CRS (P-value)	0.036	0.656	0.407
Number of observations	957	806	957
(number of firms)	151	151	151

Notes: All regressions are estimated in DPD (see Arellano and Bond, 1998); a set of year dummies is included in all models; numbers in parenthesis are two step robust standard errors; Sargan is the P-value from a test of over-identifying restrictions, which test the overall validity of instruments for the GMM estimators; Sargan-Difference is the P-value from a test of the validity of the additional restrictions imposed in the system estimator with respect to the difference estimator; m1 and m2 are the P-values from test of first and second order serial correlation; Comfac is the P-value from a test of the common factor restrictions; CRS is the P-value from a test of constant returns to scale; column (2) presents the results from a differences GMM estimator that uses as instruments $y_{it-2}...y_{it-4}$, $l_{it-2}..l_{it-4}$ and $m_{it-2}..m_{it-4}$; the results of column (3) are from a system GMM estimator with the same instruments as in column (2) plus instruments (y_{it-1}-y_{it-2}), (l_{it-1}-l_{it-2}) and (m_{it-1}-m_{it-2}).

Table 6
Food industry
Production function: alternative estimators
(dependent variable: output y_{it})

	(1) OLS	(2) Differences GMM	(3) System GMM
y_{it-1}	0.616	0.236	0.327
	(0.040)	(0.029)	(0.013)
l_{it}	0.188	0.082	0.160
	(0.040)	(0.058)	(0.017)
l_{it-1}	-0.114	-0.048	-0.042
	(0.041)	(0.039)	(0.017)
m_{it}	0.631	0.741	0.772
	(0.058)	(0.023)	(0.013)
m_{it-1}	-0.331	-0.074	-0.159
	(0.063)	(0.021)	(0.010)
k_{it}	0.031	-0.001	0.015
	(0.018)	(0.015)	(0.016)
k_{it-1}	-0.012	-0.016	-0.036
	(0.017)	(0.017)	(0.011)
Exporters_i	-0.023		-0.157
	(0.013)		(0.021)
Instruments	-	t-2	t-2 and Δ(t-1)
Sargan (P-value)	-	0.253	0.554
Sargan-Difference (P-value)	-	-	0.834
m1 (P-value)	0.091	0.002	0.001
m2 (P-value)	0.044	0.816	0.417
Comfac (P-value)	0.262	0.000	0.110
CRS (P-value)	0.006	0.001	0.492
Number of observations	1,031	872	1,031
(number of firms)	159	159	159

Notes: All regressions are estimated in DPD (see Arellano and Bond, 1998); a set of year dummies is included in all models; numbers in parenthesis are two step robust standard errors; Sargan is the P-value from a test of over-identifying restrictions, which test the overall validity of instruments for the GMM estimators; Sargan-Difference is the P-value from a test of the validity of the additional restrictions imposed in the system estimator with respect to the difference estimator; m1 and m2 are the P-values from test of first and second order serial correlation; Comfac is the P-value from a test of the common factor restrictions; CRS is the P-value form a test of constant returns to scale; column (2) presents the results from a differences GMM estimator that uses as instruments $y_{it-2}...y_{it-4}$, $l_{it-2}..l_{it-4}$ and $m_{it-2}..m_{it-4}$; the results of column (3) are from a system GMM estimator with the same instruments as in column (2) plus instruments $k_{it-2}..k_{it-4}$, $(y_{it-1}-y_{it-2})$, $(l_{it-1}-l_{it-2})$, $(m_{it-1}-m_{it-2})$ and $(k_{it-1}-k_{it-2})$.

Table 7
Timber, wooden products and furniture
Production function: alternative estimators
(dependent variable: output y_{it})

	(1) OLS	(2) Differences GMM	(3) System GMM
y_{it-1}	0.445	0.207	0.228
	(0.067)	(0.025)	(0.022)
l_{it}	0.237	0.023	0.162
	(0.049)	(0.044)	(0.023)
l_{it-1}	-0.091	0.090	-0.050
	(0.049)	(0.024)	(0.019)
m_{it}	0.604	0.632	0.699
	(0.033)	(0.025)	(0.020)
m_{it-1}	-0.181	-0.029	-0.043
	(0.041)	(0.023)	(0.018)
k_{it}	0.023	0.034	0.006
	(0.012)	(0.015)	(0.008)
k_{it-1}	-0.017	-0.014	-0.001
	(0.010)	(0.006)	(0.006)
$Exporters_i$	0.027		0.044
	(0.017)		(0.012)
Instruments	-	t-2	t-2 and Δ(t-1)
Sargan (P-value)	-	0.299	0.702
Sargan-Difference (P-value)	-	-	0.677
m1 (P-value)	0.154	0.016	0.009
m2 (P-value)	0.097	0.700	0.747
Comfac (P-value)	0.019	0.000	0.134
CRS (P-value)	0.001	0.000	0.000
Number of observations	599	502	599
(number of firms)	97	97	97

Notes: All regressions are estimated in DPD (see Arellano and Bond, 1998); a set of year dummies is included in all models; numbers in parenthesis are two step robust standard errors; Sargan is the P-value from a test of over-identifying restrictions, which test the overall validity of instruments for the GMM estimators; Sargan-Difference is the P-value from a test of the validity of the additional restrictions imposed in the system estimator with respect to the difference estimator; m1 and m2 are the P-values from test of first and second order serial correlation; Comfac is the P-value from a test of the common factor restrictions; CRS is the P-value form a test of constant returns to scale; column (2) presents the results from a differences GMM estimator that uses as instruments $y_{it-2}...y_{it-4}$, $l_{it-2}..l_{it-4}$ and $m_{it-2}..m_{it-4}$; the results of column (3) are from a system GMM estimator that uses as instruments y_{it-2}, y_{it-3}, l_{it-2}, l_{it-3}, m_{it-2}, m_{it-3}, $(y_{it-1}-y_{it-2})$, $(l_{it-1}-l_{it-2})$ and $(m_{it-1}-m_{it-2})$.