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Back to basics: The Comanor–Wilson MES index revisited

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Abstract The present article attempts to investigate the validity of the Comanor–Wilson Minimum Efficient Size (MES) measure. The basic assumption is that firms that have exhausted scale economies are in non-increasing returns to scale. The same firms are also assumed to have a size greater than MES estimated on sales (total turnover), employment or fixed assets. Data Envelopment Analysis (DEA) is used, on a sample of firms in three Greek manufacturing industries, to classify firms in operation according to increasing or non-increasing returns to scale. On the basis of the results of the DEA input oriented model, the MES measure correctly predicts over 85% of the cases. A probit model is applied to those cases that are not identically predicted by MES concerning returns to scale. Results indicate that technical efficiency, size and age are the factors that compel MES to yield the same prediction as the DEA approach.

Keywords Data Envelopment Analysis · Greek manufacturing · Minimum Efficient Size · Returns to scale

JEL Classifications L11 · L6 · D24 · L26

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1 Introduction

In the applied Industrial Organization literature, one can find a huge number of works where the Minimum Efficient Size (MES) as it was introduced by Comanor and Wilson (1967, 1969) is used to capture the effects of economies of scale on several aspects of the behaviour of firms. However, to the best of our knowledge, no work has been undertaken until now in order to test the ability of the specific measure to correctly predict the production technology regarding the economies of scale. The main research question of the present article is *to test the validity of the popular MES as a surrogate of the economies of scale*. In addition and as a second research question, we explore *the conditions under which the MES fails to correctly predict economies of scale* and thus why industrial organization researchers should use alternative, even more complex, measures.

Comanor and Wilson's (1967, 1969) seminal papers introduced an index that proxies the MES of an industry by the firm's size distribution in terms of output, invested capital and employed labour. In general, the MES indicates the degree of exploitation of the returns to scale which is more analytically presented by Davies et al. (1988, pp. 96–105) and formally defined by Varian (1999, p. 427) as "the level of output that minimizes the average cost relative to the size of demand". Due to its simplicity and ease of calculation, this index has become one of the most widely used proxies of returns to scale in industrial organization and other economics disciplines. In industrial economics the MES has been used as a major explanatory factor in many studies, of which a recent indicative list includes studies examining firm dynamics (entry and exit) and industry evolution (Agarwal and Audretsch 2001; Audretsch 1995; Audretsch et al. 2001), the effectiveness of industrial policy instruments (Huang 2002), the relative volatility between production and sales (Hall 2000) and many others. Estimations of the MES have been used extensively in the economics of innovation and R&D (Sakakibara 2001), regional economics (Rotemberg and Saloner 2000), economics of education (Scott and Anstine 2002) and farm economics (Weiss 1998), to mention only a few.

In industry dynamics research, all measures capturing scale economies such as the MES index under consideration, have been used in three distinct programmes. Scale economies measures have been used firstly, to explore barriers to entry by incumbent firms (Manjon-Antolin 2004; Geroski 1995), secondly, to determine the start-up size of infant industries (Arauzo-Carord and Segarra-Blasco 2005; Audretsch et al. 1999) and thirdly, as a major driver of firm growth (Audretsch et al. 1999; Calvo 2006; Lotti et al. 2001; Cabral 1995). In all these programmes of research, the MES and related scale economies measures, were found to play a significant role and important policy recommendations were based on the interpretation of their behaviour in econometric models.

On the other hand, Charnes' et al. (1978) seminal paper introduced Data Envelopment Analysis (DEA), a method that allows the determination of the nature of economies to scale based on the keen idea of Farrell (1957).[1] However, DEA is a nonparametric technique, highly sophisticated and data-demanding and as a result, does not render the simplicity and easiness of calculation of the MES index. The present article is organized as follows: In the second section, we combine the MES index with DEA methodology through visual devices in order to explore the correspondences regarding the prediction of economies of scale between the two approaches. Sections three and four illustrate the relationship between DEA and MES predictions using a dataset of firms from three Greek manufacturing industries. Section five concludes the article and introduces some useful suggestions to industrial economists who use the MES index to capture the effects of economies to scale in various aspects of the firms' behaviour.

2 Theoretical context: MES and DEA correspondence

As we have already mentioned, we have two alternative approaches for exploring the nature of returns to scale. The first is a very simple descriptive statistics measure introduced by Comanor and Wilson MES. The second comes from the efficiency and productivity analysis discipline, is nonparametric and is much more sophisticated than the Comanor and Wilson MES index. It is necessary to establish, however, the kind of relationship that exists between them. If MES is a credible index for the nature of returns to scale then the outcome of DEA should classify a firm's operation regarding returns to scale at the same category as the MES does. Diagrammatically speaking, in Fig. 1, the three different areas that define increasing, constant and decreasing returns to scale according to the MES index, are depicted in the average cost-output space in the case of a U-shaped with plateau cost curve. With the assistance of the 45° line, we associate these three areas to the corresponding DEA categories of returns to scale. If the MES index and DEA are consistent to each other, a firm should be classified in the same category, according to its returns to scale, by both methods. More specifically in the case when the MES index is a perfect surrogate of the economies to scale, the correspondences presented in Fig. 1 would hold. Firms which operate on a scale less (greater) than $M_1(M_2)$ (Fig. 1c), depict the DEA economies of scale, and would also correspond to a scale less(greater) than $M_1(M_1)$ in Fig. 1a, which depicts the MES economies of scale. The scales less than M_1, in both figures, correspond to increasing economies of scale, while scales greater than M_2 correspond to decreasing returns to scale. In addition, the range of scales M_1M_2 in the DEA approach would correspond to the M_1M_2 range of scale in the MES approach exhibiting constant returns to scale in the presence of a plateau of the average cost function. In the case of the non-existence of a plateau

[1] DEA development is own to Banker et al. (1984) and Färe et al. (1985). For a detailed presentation of the DEA approach see Seiford (1996), Seiford and Zhu (1999) and Cooper et al. (2006)

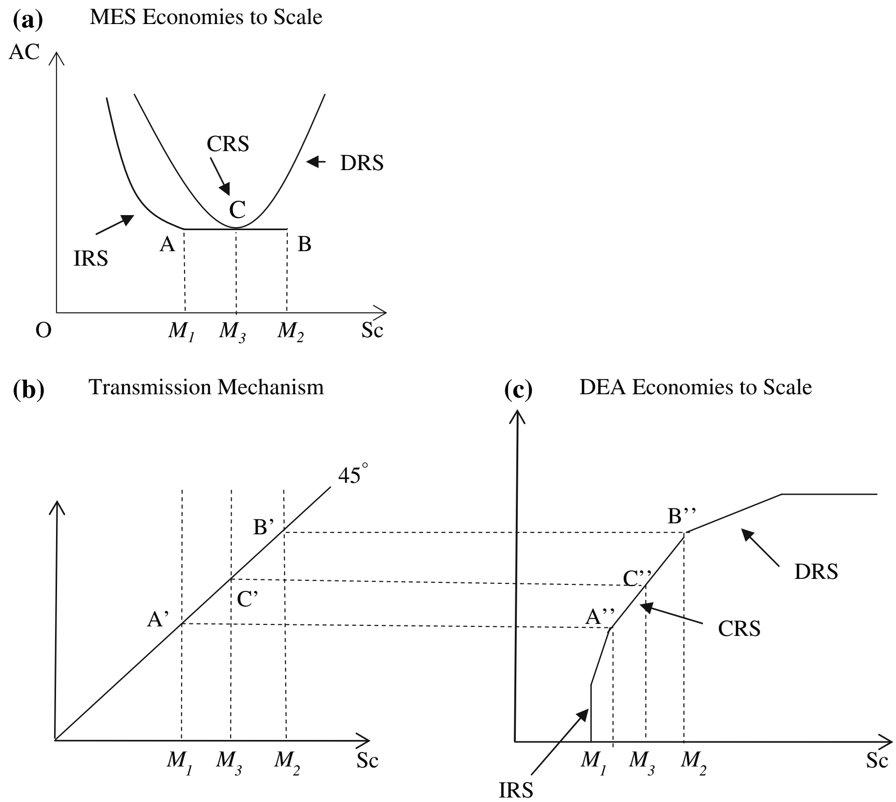

Fig. 1 Corresponding returns to scale determination between MES and DEA

the A'' and B'' coincide, and the scale M_3 is the only one which corresponds to constant returns to scale.

As we have already mentioned the MES is simpler than the DEA, MES requires simple arithmetic calculations while DEA is based on the solution of a linear programming problem. Furthermore, DEA is more data-demanding since it requires data on both output and input variables while on the other hand MES may be applied based only on an one size variable which lies either on the input or on the output side. The firms' heterogeneity with respect to underlying technology may be a problem for both approaches. The most significant advantage of the DEA approach compared to the MES may be that DEA is able to identify the plateau (a range of scales) which exhibits CRS. In contrast, following the MES approach the CRS technology corresponds only to a point estimation of all the possible scales of production.

Both approaches are appropriate for analyses mainly within a static environment, even though, a kind of dynamic analysis is not excluded. In that context, however, DEA has an advantage over the MES approach in the sense that its full panel estimates are permitted if a balanced panel of firms is available. MES can produce a time series of estimates which are not dynamic in the sense that they do not take account of a panel of observations, i.e. the history built-in observations. The DEA method is applicable only in intra-industry framework while the use of MES in inter-industry comparisons, although highly debatable, is widespread. It is not worthless to mention that DEA, although suffering from a white noise problem, is susceptible to the examination of factors which determine scale efficiency (Dimara et al. 2005). On the MES research front, to the best of our knowledge, no research examining the effect of factors on scale economies has been undertaken. This is due to the nature of MES estimates being unique for the whole industry and not firm-specific.

3 Data and variable definitions

Data for this work come from the business database maintained by the private financial and business information service company called ICAP, in Greece. The annual ICAP directories provide key elements from the published balance sheets of almost all Plc and Ltd firms operating in all sectors of economic activity in Greece. From the annual directories of ICAP, we devised a database of firms operating in three industries of the manufacturing sector, representing a relatively low tech industry, the food and drinks industry, a medium-tech industry, the printing and publishing industry and a high-tech industry, the electronics industry. The first year for which data was fully available was 1989. In order to avoid the well-recorded fluctuations of financial data due to business cycles, we constructed the means of each financial variable for each firm for the periods 1989–91 (cohort 1), 1992–94 (cohort 2), 1995–97 (cohort 3) and 1998–2000 (cohort 4). The selection of the three industries reflects different technological and market characteristics; the food industry is the largest industry and one of the most important and dynamic sectors of the Greek manufacturing industry. This particular sector is characterized by high employment and income multipliers, ranked third highest among the respective multipliers of the 35 industrial sectors of the Greek economy. The food manufacturing sector accounts for 21% of the mean annual employment, 28% of the gross production value, 26% of value-added and 30% of gross asset formation (Damianos et al. 1998, p. 41). The printing and publishing industry is one of the most rapidly developing and competitive industries in Greece, characterized by the dominance of many small firms with high dependence on capital assets. The industry's major output is produced by firms in the graphic arts section followed by firms in the newspaper and magazines section. Finally, the electrical and electronics machinery industry is relatively small but very dynamic and dominated by small specialized firms rich in human capital. In Table 1, we present basic industry dynamics for each one of the examined industries as well as the time evolution of their basic productive characteristics. It is not worthless to point out that regarding the net entry rate, we are faced with tree distinct cases. The food and beverages industry exhibits an enormous net entry from 1989 to 1998 which is set back slightly only in the period from 1998 to 2000. On the other hand, in the electronics industry the net entry is negative in the whole of the examined period. To the best of our knowledge, this reduction of the industry's population is due to a significant wave of mergers and acquisitions which took place during the 90s in the specific industry. Unfortunately there are no available data. In the case of the printing and publishing industry, one could observe a net entry phenomenon also but significantly lower than the corresponding food and beverage industry. In all of the examined industries, a positive time variation is present both in the value of produced output per firm (ΔQ), except the third period of the printing and publishing

Table 1 Industry demographics and evolution of basic productive characteristics

Period	Net Entry (Exit) (% industry population)	ΔQ per firm (%)	ΔK per firm (%)	ΔL per firm (%)
Food & beverages industry				
Cohort 1	–	–	–	–
Cohort 2	172 (26.26%)	4.45%	4.67%	−2.18%
Cohort 3	339 (40.99%)	2.21%	8.23%	−4.08%
Cohort 4	−68 (−5.83%)	11.18%	11.54%	−3.11%
Electronics industry				
Cohort 1	–	–	–	–
Cohort 2	−56 (−31.28%)	8.89%	24.08%	2.11%
Cohort 3	−17 (−12.23%)	12.12%	17.12%	3.45%
Cohort 4	−5 (−4.10%)	18.87%	15.55%	−2.54%
Printing and publishing industry				
Cohort 1	–	–	–	–
Cohort 2	−3 (−1.26%)	2.45%	3.33%	−4.88%
Cohort 3	50 (21.28%)	−1.27%	7.12%	−2.45%
Cohort 4	17 (5.96%)	6.19%	8.85%	−4.58%

industry, and of the total assets per firm (ΔK). In contrast, the average employment (ΔL) in all industries and periods, except the electronics industry in the second and third period, is persistent time declining. Thus we could argue that in all of the examined industries, the general pattern depicts firms which grow by reducing their labour input and augmenting their capital input. Apparently, input substitution is present, probably due to significant technological progress. The combination of this technological change and of industry dynamics may reflect that the firms in each industry operate under different technological regimes, of the routinized and entrepreneurial type Acs and Audretsch (1988, 1990).

Table 2 provides basic descriptive statistics for all variables used in the estimation of the firms' technical and scale efficiency scores either as outputs or inputs. The database consists of 5,363 firms of which 3,746 are active in the food industry, 1,060 in the printing and publishing industry and 557 in the electrical and electronics industry.

4 Empirical evidence

4.1 The validity of the MES index

Table 3 shows the firms' returns to scale as this is classified by MES and predicted by DEA, per industry and cohort. The first row shows the total number of firms per industry and cohort. The second and third rows show the number of firms that are classified as operating at decreasing returns to scale (MESDRS) or at increasing returns to scale (MESIRS) respectively. By definition the MES index does not allow us to identify firms operating at constant returns to scale. The next three rows show the numbers of firms predicted by DEA to operate at decreasing (DEADRS), increasing (DEAIRS) or constant (DEACRS) returns to scale. Rows seven and eight show how the MES approach classifies the firms that are predicted to operate at constant returns to scale by DEA. Row 9 shows the total number of firms for which the predictions of the MES index and of the DEA approach coincide. Rows 10 and 11 decompose this number of correctly predicted firms to increasing or decreasing returns to scale.

It is evident that the MES index is a powerful tool for identifying scale economies at firm level. The overall percentage of firms for which the MES and the DEA predictions coincide is 83.87% and ranges from 74.36% to 89.12% across industries and time periods. Thus, the predictive ability of the MES index remains high across industries with different market and technological characteristics, in different time periods, and is not affected by industry dynamics as this is portrayed by changes in the number of firms operating in an industry.

Table 3 also shows the number of firms for which DEA and the MES predictions coincide as regards

Table 2 Descriptive statistics of the variables used in the DEA

Variable statistic	(Q)*	(K)*	*(L)***	Number of firms by cohort
Food & beverages industry				
Mean	2,766.6	2,327.4	70.3	$N_1 = 655$
Std. Dev	8,663.5	7,376.7	150.2	$N_2 = 827$
Min	7.1	14.5	1.0	$N_3 = 1{,}166$
Max	835,009.3	627,643.9	1,943.8	$N_4 = 1{,}098$
Electronics industry				
Mean	659.6	722.2	21.7	$N_1 = 179$
Std. Dev	1,835.5	2,744.5	31.8	$N_2 = 139$
Min	55.3	54.8	2.0	$N_3 = 122$
Max	39,411.0	54,453.9	417.0	$N_4 = 117$
Printing and publishing industry				
Mean	2,324.3	2,468.0	55.9	$N_1 = 238$
Std. Dev	9,416.3	13,480.6	154.3	$N_2 = 235$
Min	24.5	58.9	2.0	$N_3 = 285$
Max	148,899.1	259,810.4	2,396.0	$N_4 = 302$

*In thousand Euros

**Number of employees per year

Table 3 Predicted returns to scale by industry and cohort for the MES and DEA approaches

Industry/Cohort		Electronics					Food & Beverages					P&B					Total
Prediction		1c	2c	3c	4c	Total	1c	2c	3c	4c	Total	1c	2c	3c	4c	Total	
(1)	Total No. of firms	179	139	122	117	557	655	827	1,166	1,098	3,746	238	235	285	302	1,060	5,363
(2)	DRS_{MES}	32	12	12	9	65	75	38	110	82	305	26	35	51	38	150	520
(3)	IRS_{MES}	147	127	110	108	492	580	789	1,056	1,016	3,441	212	200	234	264	910	4,843
(4)	DRS_{DEA}	39	17	23	20	99	66	23	118	2	209	20	49	51	53	173	481
(5)	IRS_{DEA}	116	114	97	82	409	531	743	949	1,010	3,233	211	176	226	242	855	4,497
(6)	Inconclusive DEA (CRS)	24	8	2	15	49	58	61	99	86	304	7	10	8	7	32	385
(7)	CRS_{DEA} as DRSMES	8	0	0	2	10	9	0	0	0	9	0	6	5	1	12	31
(8)	CRS_{DEA} as IRS_{MES}	16	8	2	13	39	49	61	99	86	295	7	4	3	6	20	354
(9)	Correctly predicted	134	114	105	87	440	535	705	989	928	3,157	199	191	254	257	901	4,498
(10)	IRS_{DEA} as IRS_{MES}	113	111	95	81	400	500	705	925	928	3,058	192	168	217	231	808	4,266
(11)	DRS_{DEA} as DRS_{MES}	21	3	10	6	40	35	0	75	0	110	7	23	37	26	93	243
(12)	Incorectly Predicted	21	17	15	15	68	62	61	78	84	285	32	34	23	38	127	480
(13)	IRS_{DEA} as DRS_{MES} (1)	3	3	2	1	9	31	38	35	82	175	19	8	9	11	47	242
(14)	DRS_{DEA} as IRS_{MES} (−1)	18	14	13	14	59	31	23	43	2	99	13	26	14	27	80	238

their returns to scale operation (row 12). Despite the fact that the percentage of incorrect predictions is low (8.95%), we examine this difference further. Row 13 shows the number of firms that are predicted to operate at increasing returns to scale by DEA (DEAIRS) and are classified as operating at decreasing returns to scale by the MES index (MES DRS), while row 14 shows the number of firms found in the exact opposite situation.

Two remarks of equal importance may be discussed regarding the difference in predictions made by the two approaches. Firms that are predicted to operate at increasing returns to scale by the DEA and decreasing returns to scale by the MES are implicitly large firms whose total value of shipments is greater than the MES. These firms do not achieve the production level justified by their size, in other words, they operate below their productive capacity, and consequently some of their inputs are, to some extent, in slack. In other words, their productive inefficiency is expected to be high.

On the other hand, firms that are predicted to operate at decreasing returns to scale by the DEA and increasing returns to scale by the MES are relatively smaller firms whose total value of shipments is smaller than the MES. These firms achieve production levels well beyond their productive capacity or, in other words, they operate by over-exploiting some of their inputs that consequently yield decreasing marginal products. Thus, we expect these firms to show high productive efficiency. The expected high efficiency can, perhaps, be attributed firstly to efforts directed in meeting short-term increase of demand, under the assumption that the price of the product will remain higher than the average cost. Secondly, it may be attributed to externally imposed constraints on the firm's growth, including financial and human capital constraints or to the concurrent effects of both sets of factors.

4.2 Exploring the discrepancies between MES and DEA concerning RTS

The above stated hypotheses may be empirically tested. Since the descriptive statistics for basic firm characteristics do not significantly differ between correctly and noncorrectly predicted firms, our interest is confined to the noncorrectly predicted firms. However, a formal test for sample selection bias did not reveal any significant selectivity bias (results of such tests are available from the authors upon request). Thus, we formulate a binary variable indicating the type of predicted difference and taking the value of one (1) if the firm is predicted to operate at increasing returns to scale by DEA (DEAIRS) and classified as decreasing returns to scale by the MES index and the value of zero (0) for the exact opposite misclassification.

Two criteria have guided the identification of the best model describing the probability that a firm will be predicted either as operating at increasing returns to scale by DEA (DEAIRS) and classified as decreasing returns to scale by the MES index or the opposite. Firstly, we looked for a meaningful and informed, from the above discussion, set of explanatory variables among the available financial and economic variables, transformations of variables or interactions among variables. These variables include firm-specific financial indices and variables of age and size, the firm's location and its exporting activity, the estimated technical efficiency, as well as control variables for industries and time periods. Basic descriptive statistics of the used explanatory variables are presented in Table 4. Secondly, we looked for the model with the best econometric properties among alternative models. This implies that variables with no statistically significant results have been included in our final model, as they are also regarded to be an important finding.

Table 4 Descriptive statistics of the variables used in the probit model

	AGE	SIZE	VRSTE	IND2*	IND3	Coh1	Coh2	Coh3
Mean	25.5	184.51	0.318	=1: 59.37% =0: 40.63%	=1: 73.55% =0: 2645%	=1: 76.04 =0: 23.96	=1: 76.67 =0: 23.33	=1: 75.83 =0: 21.17
Std. Dev	21.1	309.4	0.289					
Min	1.0	1.0	0.001					
Max	122.0	1,943.7	1.000					

*Frequencies are reported for dummy variables

Separate tests examining the null hypothesis that individual coefficients are zero (0), and a joint test of the null hypothesis that all the parameters associated with the explanatory variables equal zero (0) have been performed. A goodness-of-fit measure usually reported as McFadden's pseudo-R^2 measure, or rho-square ρ^2 (Maddala 1983), is also computed. Maximum likelihood estimated coefficients, their corresponding asymptotic standard errors, the chi-square test and the ρ^2 goodness of fit measure are shown in Table 5.

The percentages of correctly predicted cases by this binary model are shown in Table 6.

The chi-square test is highly significant and the corresponding goodness-of-fit ρ^2 measure indicates a satisfactory fit. The model correctly predicts 90.62% (435 out of 480) of the outcomes. Specification test analysis involves a test for homoscedasticity (Greene 1997, p. 890), and a test for the omission of certain variables. Omission of a significant variable, in the context of a binary, dichotomous choice model, implies that even if the omitted variable is uncorrelated with the one being included, the coefficient on the variable being included will be inconsistent (Yatchew and Griliches 1984). Our test for variable omission included the firm's location and exporting activity and various financial indices of the firm (ROA, ROI, leverage, burden debt, etc.).

Table 5 Probit model estimation results

Variable	Coefficient value	Standard error	Prob(|Z|>z)
Constant	−2.072	0.562	0.000
AGE	0.011	0.004	0.002
SIZE	0.015	0.002	0.000
VRSTE	−1.825	0.409	0.000
IND2	0.715	0.319	0.025
IND3	1.426	0.318	0.000
Coh1	−0.108	0.247	0.662
Coh2	0.098	0.279	0.724
Coh3	0.077	0.253	0.760
Fit measures			
Log-L	−131.292	Re str. Log-L	−332.694
X^2	402.804	McFadden's ρ	0.577

Table 6 Frequencies of actual and predicted outcomes

Actual	Predicted		
	0	1	Total
0	225 (94.53%)	13 (5.46%)	238 (100.00%)
1	32 (13.22%)	210 (86.78%)	242 (100.00%)
Total	257 (53.54%)	223 (46.46%)	480 (100.00%)

The sign of the coefficient of a firm's technical efficiency (VRSTE) implies that a highly technical efficient firm is less probable to be classified as operating at decreasing returns to scale by the MES index (MESIRS) while it is predicted to be operating at increasing returns to scale by DEA (DEADRS). Likewise, as the technical efficiency decreases, the probability that the opposite holds, increases.

Thus, one may argue that the MES index does produce the same predictions as the DEA method as concerns the nature of returns to scale in two cases. Firstly, when highly technical efficient but small firms are considered and secondly, when large but relatively technically inefficient firms are considered. This is due to the fact that the nature of returns to scale derived by the MES index is based solely on the value of a firm's output while the DEA methodology takes into account the weighted ratio of output to inputs and, as such, the volume and value of output is 'corrected' by the bundle of inputs used to produce it.

The sign of the coefficient of the size variable (SIZE) reconfirms the above finding and indicates that, for relatively large firms which by definition are accounted as operating at decreasing returns to scale by the MES index, the DEA methodology predicts the opposite. For relatively small firms, the opposite holds true (Cabral 1995). The sign of the coefficient of the variable showing the firm's age (AGE) shows that older firms are more probable to be predicted as operating at decreasing returns to scale by MES (MESDRS) and as operating at increasing returns to scale by DEA (DEAIRS) (Cressy 2006). In that case one may argue that the age variable captures accumulated learning effects of the relatively larger firms that allows them to operate at increasing returns to scale despite the fact that, at some point in the past, these firms may had been operating at decreasing returns to scale. Industry effects (IND2, IND3) are statistically significant showing that inter-industry differences are significant factors influencing the type of incorrect prediction. This may be attributed to different technological regimes, business strategic behaviour and competitive conditions as well as to differences in industrial conventions (Audretsch et al. 1999; Lotti et al. 2001; Acs and Audretsch 1989). On the contrary, the type of prediction seems to be time persistent since cohort effects (Coh1, Coh2 and Coh3) are statistically nonsignificant.

5 Conclusions

The overall judgement is that the MES index is a valid tool for identifying economies to scale at firm level, and thus its widespread use is, to a great extent, justified. Furthermore, its predictive ability remains high across industries with different market and technological characteristics, in different time periods, and is not affected by changes in the number of firms operating in an industry. A word of warning should be addressed when the MES is used for sectors that do not operate under the conditions of practical competition.

An equally important result is found when the firms that are not predicted in the same way by both the MES and DEA are examined. The first case concerns firms that are predicted as operating at increasing returns to scale by DEA and at decreasing returns to scale by the MES, implying that these are large firms, i.e. their value of total shipments is greater than the MES, but do not achieve the production level allowed by their size, which indicates that they operate below their productive capacity, and therefore, some of their inputs are, to some extent, in slack. The second case concerns firms that are predicted to operate at decreasing returns to scale by DEA and increasing returns to scale by the MES, implying that these are relatively smaller firms, i.e, their value of total shipments is smaller than the MES, but these firms achieve production levels well beyond their capacity, which indicates that they operate by over-exploiting some inputs that correspondingly yield decreasing marginal products. Detailed empirical investigation into the reasons causing the aforementioned discrepancies revealed that a firm's technical efficiency, size and age are the underlying factors driving the type of difference in prediction by the two approaches. More specifically, high technical efficiency in the form of higher managerial ability allows smaller firms, which are otherwise predicted to operate at increasing returns to scale by the MES index, to exhaust scale effects. In the case of the effects exerted by the firms' age and size, the opposite outcome is observed. Thus, in sectors where there are strong indications that the above discussed discrepancies may be widespread, the MES index may not be the correct choice.

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