Firms' size and productivity in Spain: a stochastic frontier analysis[*].

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Abstract:

This paper analyses the performance of the small and medium manufacturing firms during the period 1995-2001, focusing on the degree of technical inefficiency and its determinants. We use a micro panel data set to estimate simultaneously a stochastic frontier production function and the inefficiency determinants using an unbalanced panel of manufacturing firms. Our empirical results suggest that small and medium firms tend to be less inefficient than the large firms are. Also we centre our analysis in the effect on efficiency of some organisational factors related to the managerial ability to use and adjust properly capital and labour.

KEYWORDS: Stochastic frontier; panel data; technical efficiency, size and organisational factors.

JEL: C23, J21, J29 and L60

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1. Introduction.

Searching for explanations for the slowdown in productivity growth in Spain occurred between the middle of 1995 and the end of 2000 economists have analysed real factors, as well as possible measurement problems. But most of these debates have been focused on technological innovation, leaving aside human and organisational factors. One of the characteristics of the Spanish economy is the high percentage of small and medium firms. The size is one of the factors that conditioning the managerial organisation of the firm, so it is important to understand the effect of it into productivity.

Changes in productivity are regarded as consequences of two different factors. On the one hand, the adoption of technical innovations in processes and in products, pushing the frontier of potential production upwards, is measured by technological progress. On the other hand efficiency change reflects the capacity of firms to improve production with given inputs and available technology. While productivity and technical efficiency are not easily separable, the distinction allows us to test different factors that are supposed to be at the root of these two indicators of performance.

We are interested in analysing the determinants of the technical efficiency in the Spanish manufacturing firms. Efficiency determinants can be due to environmental or firm specific factors. We focus on these firms’ specific factors to provide an explanation to the differences in technical efficiency among manufacturing firms.

We follow the frontier approach, first developed by Farrell (1957) and widely used in empirical works for specific activity sectors[i]. This approach measures the technical inefficiency of a production unit as the ratio of a firm's production over its optimal level. The optimal behaviour, the technically efficient result of the production process, is represented by a production function, a frontier, which shows the maximum level of output a firm can achieve, given the technology and a given level of inputs. The first step of this approach is to estimate the practice frontier obtained from the sample information, using their best observations. If a firm produces this optimal level of output, it is technically efficient and it will be on the frontier. If a firm produces less than it is technically feasible, given both, the technology and a level of inputs, it is inefficient and we can measure the degree of technical inefficiency as the distance from each individual observation and a corresponding point on the frontier. We use the Battese and Coelli, 1995 model to estimate simultaneously the frontier production function and the inefficiency model, to avoid the econometric problem of the two-steps procedure.

Studies by Gumbau (1998), Gumbau and Maudos (2002) and Martín-Marcos and Suárez-Gálvez (2000) provide evidence on the existence of technical inefficiency on production in the Spanish manufacturing sector. Others focus on particular determinants of efficiency; for instance Delgado et al (2002) centre on the relation between efficiency and export; Díaz and Sánchez (2004) examine the link between technical efficiency and the labour force composition. With other econometrics techniques Fariñas and Ruano (2004) measure the contribution of continuing firms and turnover to total factor productivity; Huergo and Jaumandreu

(2004) analyses the probability of introducing innovations by manufacturing firms at different stages of their lives. All of them use the EESE data set (Encuesta sobre Estrategias Empresariales) of Spanish manufacturing firms.

The purpose of this paper is to analyse the effect on efficiency of some organisational factors related to the managerial ability to use properly and adjust capital and labour according to the environmental conditions. Size is included in the analysis as one of the most important factors that condition organisation of firms and then the degree of their efficiency.

Our paper contributes to the empirical evidence of productivity in Spain adding to the previous papers the relevance of changes affecting the factors of production and the way these factors are used and combined. Secondly, our paper differ from the previous literature in Spain because we use an improved frontier model that not only allows us to estimate the firm's technical inefficiency but, simultaneously, identify the variables that are statistically related to inefficiency, that is, the determinants of the reached inefficiency.

We examine the evolution of individual firm technical efficiency during the period 1995-2001 and analyse their determinants through an unbalanced panel of 1973 firms. We use an improved version of the Stochastic Frontier Approach (SFA), developed by Battese and Coelli (1995), which allow us to estimate simultaneously individual technical efficiency scores and the significance of a series of variables that can affect the level of efficiency reached by firms.

The paper is organised as follows: Section two introduces the econometric method of estimation. In section three we describe the sample, the data and define the variables used for estimation. In section four we present the estimated frontiers and explain the effects of the inefficiency determinants. Finally, in section five we summarise the main conclusion.

2. Stochastic frontier and the inefficiency model

We use the SFA to estimate a production frontier with inefficiency effects. Specifically, we use a panel data version of Aigner et al. (1977) approach, following the Battese and Coelli (1995) specification, in which the technical inefficiency is estimated from the stochastic frontier and simultaneously explained by a set of variables representative of firms' characteristics. This approach avoids the inconsistency problems of the two-stage approach used in previous empirical works when analysing the inefficiency determinants[ii].

The Battese and Coelli (1995) model can be expressed as:

$$Y_{it} = f(X_{it};\beta)\exp(v_{it} - u_{it}) \tag{1}$$

Where X is the set of inputs; β is the set of parameters, v_{it} is a two-sided term representing the random error, assumed to be iid $N(0, \sigma^2)$; u_{it} is a non-negative random variable representing the inefficiency, which is assumed to be distributed independently and obtained by truncation at zero of $N(\mu_{it},\sigma^{2})$. The mean of this distribution is assumed to be a function of a set of explanatory variables: $\mu_{it} = \delta_i Z_{it}$ and then, the inefficiency term is:

$$u_{it} = \sum_{i=1}^{11} \delta_i Z_{it} + W_{it} \quad (2)$$

Where Z_{it} is a (Mx1) vector of variables that may have effects over firm efficiency, δ_i is a (1xM) vector of parameters to be estimated and W_{it} is a random variable defined by the truncation of the normal distribution with zero mean and variance σ^2.

The production function coefficients (β) and the inefficiency model parameters (δ) are estimated by maximum likelihood together with the variance parameters: $\sigma_S^2=\sigma^2/\sigma_v^{\ 2}+\sigma^{\ 2}$ and $\gamma=\sigma^{\ 2}/\sigma_S^2$.

Given that technical efficiency is the ratio of observed production over the maximum technical output obtainable for a firm (when there is not inefficiency), the efficiency index (TE) of firm *i* in year *t* could be written as[iii]:

$$TE = \frac{f(X_{it};\beta)\exp(v_{it} - u_{it})}{f(X_{it};\beta)\exp(v_{it})} = \exp(-u_{it}) \quad (3)$$

The efficiency scores obtained from expression (3) take value one when the firm is efficient and less than one otherwise.

3. Data and variables

The Data source is published in the Spanish Industrial Survey on Business Strategies (Encuesta sobre Estrategias Empresariales, ESEE). The data is collected by the Fundacion Empresa Pública (FEP) and sponsored by the Spanish Ministry of Industry. It is supplied as a panel of firms' representative of twenty manufacturing sectors. A characteristic of the data set is that firms participating in the survey were chosen according a selective sampling scheme. The sample of firms includes almost the universe of Spanish manufacturing firms with more than two hundred employees. Firms employing between ten and two hundred employees were chosen according to a stratified random sample representative of the population of small firms. Given the procedure used to select firms participating in the survey, both samples of small and large firms can be considered as samples that allow us to estimate the distribution of any of the characteristics of the population of Spanish manufacturing firms with available information of our data set. Each year a number of entering firms were selected according to a random sampling procedure among the whole population of entering firms. This selection is conducted using the same proportion as in the original sample (see Fariñas and Jaumandreu (1999) for technical details of the sample)

From the original sample, a number of firms have been eliminated, most of them for the lack of relevant data. Others because they reported annual growth rate of value-added by worker bigger than 500% (in absolute value); or because they have a number of workers small than ten and, in both cases, they will distort the analysis. Our sample includes 1973 firms from the ESEE Survey and refers to an unbalanced panel where we have drop out those firms without two consecutive years. Firms with a number of workers from ten to two hundred workers represent the 68.9% of our sample. Our period of analysis is from 1995 to 2001.

We estimate a stochastic translog production function adding a term of inefficiency, whose mean is a function of a set of inefficiency determinants:

$$\log Y_{it} = \beta_0 + \sum_{i=1}^{3} \beta_i x_{it} + \frac{1}{2}\sum_{i=1}^{3} \sum_{j=1}^{3} \beta_{ij} x_{ijt} + \sum_{i=1}^{6} \varphi_i S_{it} + \sum_{i=1}^{3} \phi_i d_{it} + $$
$$+ v_{it} - u_{it} \tag{4}$$

$$u_{it} = \sum_{i=1}^{11} \delta_i Z_{it} + W_{it} \tag{5}$$

The variables used for estimation of the production frontier are the value-added, as the output variable, and the number of employees of the firm, capital stock and trend, as input variables (x_{it}), the industrial sectors dummies (S_{it}) and three dummy variables reflecting if firms have been affected by a process of division or a merger (d_{it}). Here we present a more precise definition of the variables used for estimation and the definition of the inefficiency determinants considered:

Variables of Stochastic Frontier estimations:

VA: The value added in real terms. This is dependent variable.

CAPITAL STOCK (K): Inventory value of fixed assets excluded grounds and buildings.

L: Total employment by firm.

T: This is the time trend.

Sector classification:

SEC1: **Meat and manufacturing of meat; food industry and tobacco drinks; textile, clothing and shoes; leather, shoes and derived**. This is a dummy variable that takes value one when the firm belongs to this sector of activity, zero otherwise. This is the category of reference.

SEC2: **Wood and derived, paper and derived.** This is a dummy variable that takes value one when the firm belongs to this sector of activity, zero otherwise.

SEC3: **Chemical products; couch and plastic; non-metallic mineral products.** This is a dummy variable that takes value one when the firm belongs to this sector of activity, zero otherwise.

SEC4: **Basic metal products; fabricated metal products; industrial equipment**. This is a dummy variable that takes value one when the firm belongs to this sector of activity, zero otherwise.

SEC5: **Office machinery and others; electric materials.** This is a dummy variable that takes value one when the firm belongs to this sector of activity, zero otherwise.

SEC6: **Cars and engine; other material transport.** This is a dummy variable that takes value one when the firm belongs to this sector of activity, zero otherwise.

SEC7: **Others manufacture products.** This is a dummy variable that takes value one when the firm belongs to this sector of activity, zero otherwise.

MERGER: Is a dummy that takes values one if the firm has been involved in a merger process and zero otherwise.

DIVISION 1: Is a dummy that takes value one if the firm has suffer a division and keep the main structure of the old firm and zero otherwise.

DIVISION2: Is a dummy that takes value one when the firm has been split up and it is identify as a new firm and zero otherwise.

Determinants of efficiency' estimation:

TEMPORARY WORKERS' PROPORTION: It is the proportion of temporary over permanent workers.

FOREING SHAREHOLDERS: Is a dummy that takes value one when the firm has foreign shareholders and zero otherwise.

MARKET SHARE: Is the ratio of the sales of an individual firm over the sector sales by year.

CAPITAL BY WORKER: It is the capital-total labour ratio.

GROSS INVESTMENT OVER CAPITAL: This is the ratio between gross investments over capital by firm.

PUBLIC LIMITED COMPANY: This is a dummy variable that take value one when the firm is a public limited company and zero otherwise.

SIZE 1: This is a dummy variable that takes value one when the firm has no more than twenty workers, zero otherwise.

SIZE 2: This is a dummy variable that takes value one when the firm has a number of workers that range between 21 up to 50.

SIZE 3: This is a dummy variable that takes value one when the firm has a number of workers that range between 51 up to 100.

SIZE 4: This is a dummy variable that takes value one when the firm has a number of workers that range between 101 up to 200.

SIZE 5: This is a dummy variable that takes value one when the firm has a number of workers that range between 201 up to 500.

SIZE 6: This is a dummy variable that takes value one when the firm has a number of workers higher than 500.

4. Results.

From the frontier approach we obtain the measure of firm's inefficiency compared with the best observations of the sample. The value of the estimates allows us to explain the differences in the inefficiency effects among the firms. As technological and market conditions can vary over sectors we have included sector dummy variables in the production function to control it.

The maximum-likelihood estimates of the production frontier parameters, defined in equation (4), given the specification for the inefficiency effects, defined in equation (5), are presented in Table I. These estimates were obtained using the computer program FRONTIER 4.1 (Coelli (1996)). Table II presents the tests of the null hypotheses, based on the generalised likelihood ratio (LR) test[iv], concerning the selection of the functional form and the relevance of the inefficiency effects.

TABLE I

TABLE II

The functional specification of the stochastic production frontier was determined by testing the adequacy of the translog specification to the data relative to the more restrictive Cobb-Douglas. The first line of Table II reports this test, where the first null hypothesis is rejected showing that the translog specification fits the data better than the Cobb-Douglas.

The variance parameter, γ which lies between 0 and 1, indicates that technical inefficiency is stochastic and it is relevant to obtain an adequate representation of the data. The value of γ picks up the part of the distance to the frontier explained for the inefficiency. In our estimation, the value of the variance parameter γ is around 0.88. That means that the variance of the inefficiency effects is a significant component of the total error term variance and then, firms deviations from the optimal behaviour are not only due to random factors. The stochastic frontier with inefficiency effects is a more appropriate representation than the standard OLS estimation of the production function.

The second test reported in Table II reinforces the relevance of the inefficiency effects in the model. The null hypothesis, which considers that the inefficiency effects are not present in the model, is strongly rejected. Then, the frontier model could not be reduced to a mean-response production function (OLS estimation) to represent accurately the data.

The third test picks the jointly effect of the determinants included in the inefficiency model. We strongly reject the null hypothesis that means that these determinants are not relevant to explain inefficiency.

*4.1. **Efficiency analysis of the Spanish manufacturing firms***

The analysis of efficiency is important because is a component of productivity and from the structural approach[v] point of view productivity is a long run determinant of competitiveness, then there is a link between efficiency and competitiveness. Since Spain belongs to UE more attention has received the structural aspect of competitiveness, that is, productivity and its determinants: management organisation, innovation, the endowment of labour and capital and the degree of use, market competition etc. These determinants have been included in the analysis to know their relevance of the degree of inefficiency in Spain.

The inefficiency tends to be larger for firms with a high ratio of temporary over fixed workers (**Temporary workers' proportion**). The positive sign of the estimated parameter means that the higher the ratio the lower technical efficiency is (higher inefficiency). Temporary contracts became attractive to employers because of their short duration and low severance payment. The great difference in severance payments between temporary and permanent contract is a key to understanding their success (see Dolado et al, 2002). However in Spain, even if job creation increased temporary contracts, no permanent employment was created because renewal rates within permanent contracts were very low (see Amuedo-Dorantes, 2001; and Güell and Petrongolo, 2000). Temporary contracts can have a positive effect on effort if workers perceive that the rehiring probability depends on past performance. If the renewal's rate is low, firms and workers may be less inclined to invest in specific human capital, what imply that workers with temporary contracts will tend to receive less training and it will affect their productivity. This result is in favour of the hypothesis of the absence of incentives and training. Thus, following the efficiency wage framework, this type of contracts would diminish productivity because workers perceive that their effort will not be recognised.

The variable **foreign' shareholders** identify firms with foreign capital. We expect that firms oriented towards international markets would be more efficient than those mainly focused on domestic markets. The coefficient of this variable is negative and significant affecting positively efficiency. This variable could be a proxy of the degree of competitiveness of firms. The market selection' hypothesis is an explanation of our result. The exporting firms have a greater productivity and this fact explains why they could attract foreign capital. This correlation have been recently analysed by Delgado, Fariñas and Ruano, 2002. This hypothesis implies that only the most productive firms survive in the highly competitive export market.

The **market share**, defined as firm sales over total sector sales, is significant and shows a negative sign, which means that as higher is the market share the lower is the inefficiency of the firm. This variable captures the relevance of the market power of the firm inside its sector.

Unexpectedly, the intensity of capital (**capital by worker**) is positive and significantly different from zero, which means, the higher intensity of capital the lower the level of firm's efficiency is. This variable picks the effect on efficiency of the combination of inputs. One possible explanation is that changes in efficiency generated by a technical innovation depend on their nature and diffusion. If it is easy for firms to adopt a technical innovation, then this change affects positively the efficiency while, if it requires an important investment as well as organisational modification then it could cause a shift in the frontier, so the relative distance augment. It means that, even if an increase in the stock of capital improves efficiency to do it in a different timing than the rest of the firms could causes loses of productivity derived of the capital adjustment in the short-run.

The variable **gross investment over capital** is negative but it is not significantly different from zero, which means that this variable do not contribute to explain firms' inefficiency.

Public Limited Company is negative and significant which means that this kind of firm organisation is the most efficient.

Now we will analyse the **size** of the firm in terms of workers. In our results we find a negative and significant relationship between size and efficiency. The effect of the size on efficiency also is reported in the Figures from 1to 7 that appear in the Appendix. These figures show the efficiency index by size and year of estimation. The firms with high degree of efficiency are grouped around two sizes: one small for workers between 21 and 50 and other medium for firms with a number of workers that rang among 201 to 500.

If large firm size allows for the realisation of costs advantages, the relationship between size and technical efficiency should be positive. However there are at least two reasons for expecting a negative relationship. First, large firms may suffer more from bureaucratic frictions and lacking motivation of workers, difficulty in monitoring than smaller firms. Second, large firms are more able to remain in the market even if they have economic problems due to a low technical efficiency than small firms because of the existence of market imperfections. Due to this effect of market selection, the surviving small firms that we observe may on average show a higher level of technical efficiency than the larger firms may.

4. Concluding remarks

In this paper we were interested in analysing the determinants of the technical efficiency in the Spanish manufacturing firms. Efficiency determinants can be due to environmental or firm specific factors. We focus on these firms' specific factors to provide an explanation to the differences in technical efficiency among manufacturing firms. Small and medium firms seem to be more efficient than large firms are. This result could be explained by the complexity of larger firms in organisation and managerial control. Also the less efficient small firms will exit the market under economics difficulties more easily than large firms will. This self-selection hypothesis explains that small firms could appear as more efficient in our analysis.

Also, the inefficiency tends to be smaller for firms with a small proportion of temporal workers, when the firm has a higher market share and when it obtains foreign capital. The later result could be explained through the market selection hypothesis as the explanation of a greater productivity.

Summing up, after controlling for market share, foreign shareholders, the proportion of temporary over fixed workers, the intensity of capital and firm legal status, we have obtained that small and medium firms tend to be more efficient than large firms are.

[i] Specially, sectors as banking, agriculture, transport and electricity industries, hospitals and other non-profit sectors, see Lovell (1993) for a good survey of the frontier approach.

[ii] In a two-stage procedure, firstly, a stochastic frontier production function is estimated and the inefficiency scores are obtained under the assumption of independently and identically distributed inefficiency effects. But in the second step inefficiency effects are assumed to be a function of some firm-specific variables, which contradicts the assumption of identically distributed inefficiency effects.

[iii] Individual efficiency scores $u_{i,}$ which are unobservable, can be predicted by the mean or the mode of the conditional distribution of u_i given the value of $(v_i\text{-}u_i)$ using the technique suggested by Jondrow et al (1982).

[iv] $LR=-2\{\ln[L(H_0)]-\ln[L(H_1)]\}$, where $L(H_0)$ and $L(H_1)$ are the values of the likelihood function under the null and alternative hypotheses. LR has an approximately chi-square distribution with degrees of freedom equal to the number of restrictions.

[v] For a deep analysis of the determinant of competitiveness in the Spanish economy see Bravo, S. and Gordo, E (2003).

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Table I: Stochastic Frontier Analysis.
Translog Production function estimates.

Variables		Coefficient	Standard-Error	T- Student
Constant	β_0	3,162	0,067	47,189
K	β_1	0,004	0,018	0,217
L	β_2	1,063	0,031	33,799
T	β_3	0,016	0,014	1,192
k^2	β_{11}	0,043	0,002	17,900
L^2	β_{22}	0,051	0,008	6,844
T^2	β_{33}	-0,001	0,001	-0,438
KxL	β_{12}	-0,092	0,008	-11,653
KxT	β_{13}	-0,002	0,002	-0,770
LxT	β_{23}	0,001	0,004	0,199
Wood and derived, paper and derived.	φ_1	0,186	0,017	11,106
Chemical products; couch and plastic; non-metallic mineral products.	φ_2	0,216	0,014	15,838
Basic metal products; fabricated metal products; industrial equipment.	φ_3	0,279	0,013	20,786
Office machinery and others; electric materials.	φ_4	0,274	0,018	15,160
Cars and engine; other material transport.	φ_5	0,138	0,019	7,098
Others manufacture products.	φ_6	0,111	0,020	5,651
Merger	ϕ_1	0,065	0,035	1,857
Division1	ϕ_2	0,072	0,054	1,354
Division2	ϕ_3	-0,297	0,088	-3,385
Inefficiency model				
Constant	δ_0	-1,756	0,268	-6,556
Temporary workers' proportion	δ_1	0,102	0,009	11,076
Foreign shareholders	δ_2	-3,789	0,315	-12,012
Market share	δ_3	-1,564	0,225	-6,943
Capital by worker	δ_4	0,002	0,000	11,616
Gross investment over capital	δ_5	-0,003	0,003	-1,077
Public limited company	δ_6	-1,266	0,101	-12,525
Size1: Up to 20 workers	δ_7	-1,010	0,090	-11,231
Size2: From 21 to 50	δ_8	-1,413	0,124	-11,399
Size3: From 51 to 100	δ_9	-1,372	0,120	-11,473
Size4: From 101 to 200	δ_{10}	-0,268	0,061	-4,367
Size5: From 201 to 500	δ_{11}	-0,920	0,084	-10,953
Variance Parameter				
	σ^2	1,141	0,087	13,080
	γ	0,879	0,010	91,736

Table II: Generalised likelihood-ratio (LR) tests of null hypotheses [a]

Null hypothesis, H_0	Test Statistic	Critical value
H_0:β_i=0, i=4,....,10	467.97	12,59
H_0: $\gamma=\delta_0=......=\delta_{11}=0$	778.46	20,4 [b]
H_0: $\delta_1=......=\delta_{11}=0$	328.64	19,68

[a] The test statistics have a χ^2 distribution with degrees of freedom equal to the difference between the parameters involved in the null and alternative hypothesis.

[b] As γ takes values between 0 and 1, in H_0: $\gamma=\delta_0=......=\delta_{11}=0$ the statistic is distributed according to a mixed χ^2 whose critical value is obtained from Kodde and Palm (1986).

Efficiency by year and size:

Figure 1

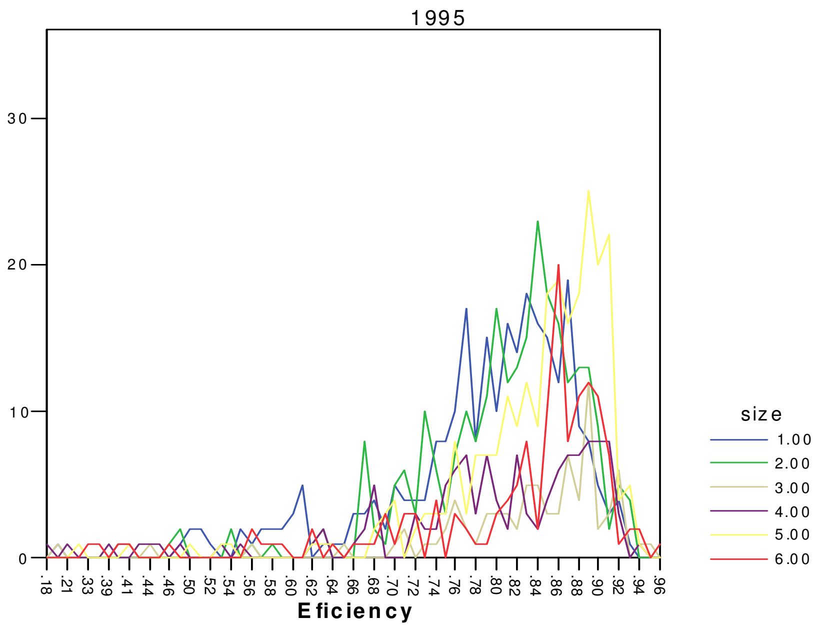

Figure 2

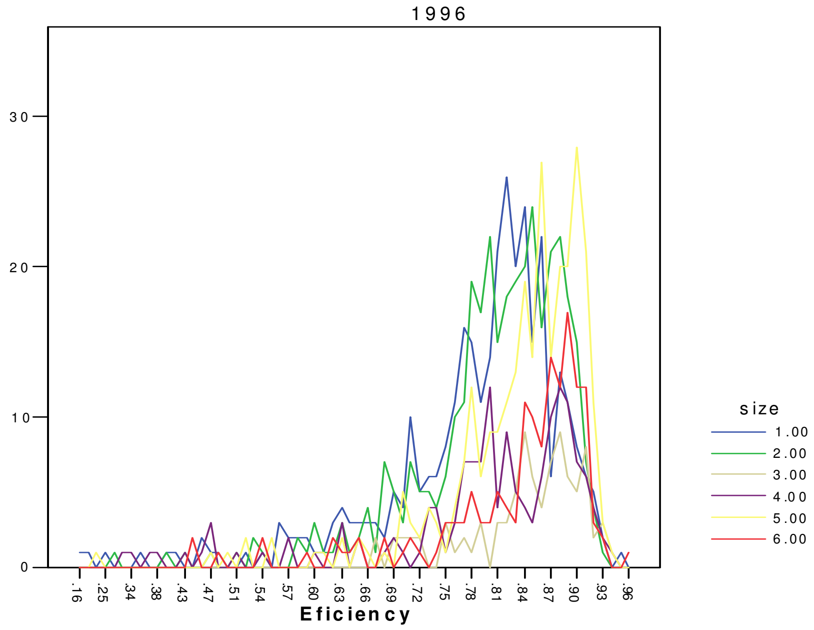

Figure 3

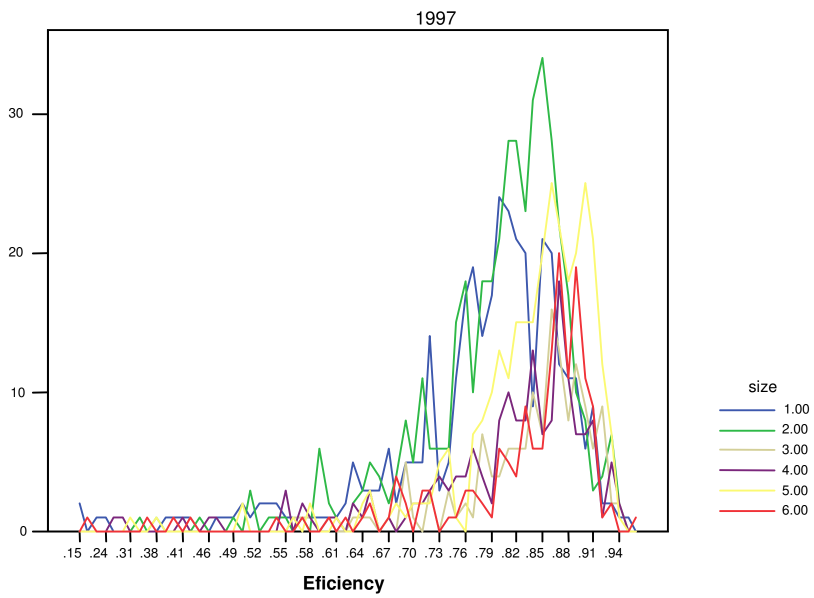

Figure 4

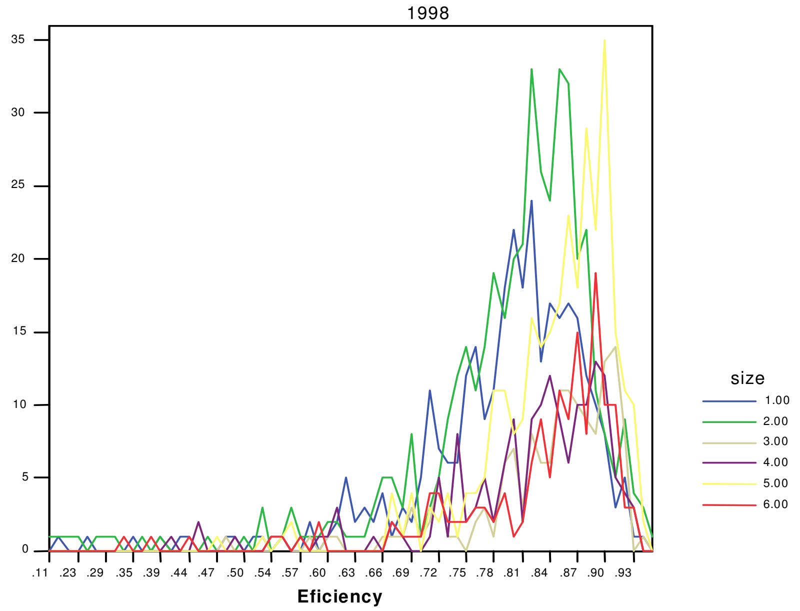

Figure 5

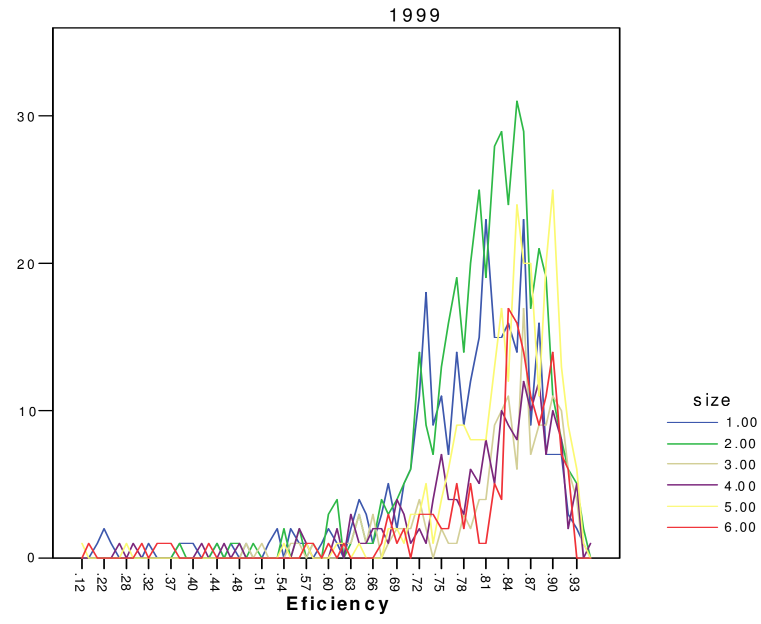

Figure 6

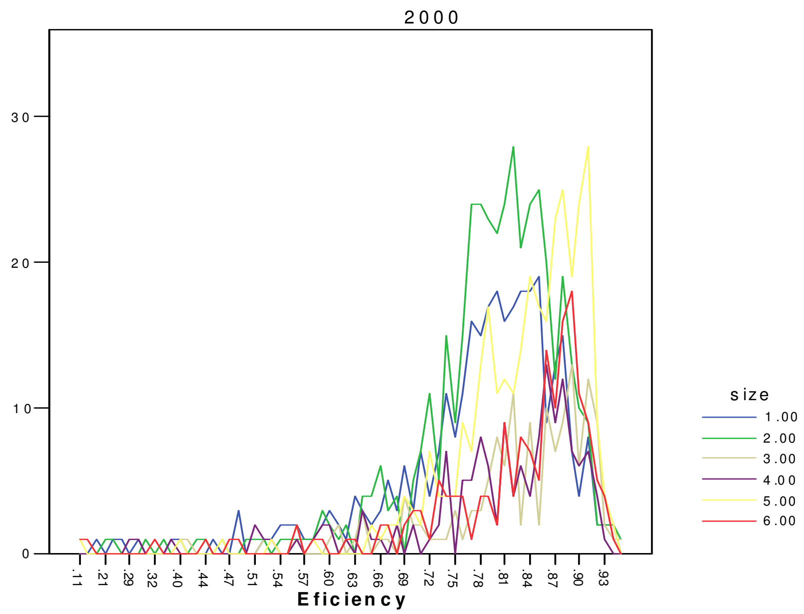

Figure 7