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Linking and Weighting Efficiency Estimates with Stock Performance in Banking Firms

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Linking and Weighting Efficiency Estimates with Stock Performance in Banking Firms [1]

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Abstract: The purpose of this paper is to contribute further evidence on bank efficiency by defining alternative efficiency measures which are linked to market returns of financial institutions. Given a series of functions (production costs, opportunity costs of capital with systematic risk, opportunity cost of capital with specific risk, and branch network distribution), we estimate alternative partial measures of bank efficiency. Assuming that these functions are related to market returns on shares, an estimation of the relative importance of each of the functions is carried out, considering an additional initially unknown function which can be attributed to individual differences not accounted for in the previous four definitions. Due to the nature of the model, strong collinearity may be expected among efficiency measures. With the aid of a tabu search procedure, artificial instrumental variables are generated which avoid collinearity and permit the isolation of the underlying relationships. Results are applied to all Spanish banks quoting on the stock exchange in 1994.

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1. INTRODUCTION

Imperfections in markets lead to the existence of alternative means of undertaking transactions against one way in would-be perfect markets. Some forms of transaction will be more efficient than others. The long-term survivorship of intermediaries depends on how efficient these intermediaries are at reducing market imperfections. However, reduction of a particular imperfection will imply the increase of another at the efficient frontier, where all combinations of the frontier are Pareto optimal. Those intermediaries that adopt a form that is at the efficient frontier will continue to survive and expand.

While efficiency in markets is measured by the amount and speed with which information is incorporated into prices, firm efficiency depends upon the way it produces output from inputs. Producing more outputs than competitors for the same amount of inputs, or consuming less inputs for the same amount of output is a sign of relative efficiency.

In a semi-strong, efficient market where most of the information is incorporated into prices, stock value performance is, as it is widely accepted (Brealey and Myers, 1991, pp 915), the best measure of estimating whether firms are creating value for shareholders or not. It may be expected that efficient firms perform better than inefficient firms and this fact will be reflected in market prices (directly through lower costs or higher output or indirectly, through higher customer satisfaction and higher prices which in return may improve stock performance). However, there may be efficiency criteria that are not important or relevant to the market, that is to say, the firm may be more efficient in a particular criterion than its competitors but the market does not value this efficiency. Hence, the firm is not creating value by being efficient in this particular criterion. Alternatively, all firms within an industry may be efficient in a particular criterion and, though highly valued by the market, it is not a distinctive factor among firms and hence there would not be stock performance differences due to this criterion.

In the search for firm efficiency, the particular attributes in the input-output field which convey a competitive advantage to a financial institution have been analyzed by researchers. There is little consensus (Clark, 1988; Humphrey, 1990; Berger, Hunter and Timme, 1993) concerning the extent or existence of scope or product mix efficiency. The widely divergent estimates of optimal scope economies provide little support for a conclusion of global economies of scope. In addition, Berger, Humphrey and Pulley (1996) do not find evidence of revenue economies of scope. The fact should also be taken into account that heterogeneity among banks in terms of size and output mix decreases the precision of equation estimates and measures of bank efficiency calculated from said banks (McAllister and McManus, 1993).

Firm efficiency measures vary depending on the cost definitions and the estimation methodology. Emphasis has been given to the comparison of alternative frontier cost efficiency methodologies (Cummins and Zi, 1997; Resti, 1997) which can be classified into econometric studies and mathematical techniques. In Cummins and Zi (1997) multiple econometric and mathematical techniques are compared. It is shown that while for absolute values there are significant differences among econometric techniques, the rankings obtained are quite similar among econometric estimates. More disparity is observed when comparing the mathematical techniques. On the other hand, Resti (1997) finds that econometric and mathematical techniques are similar in results and that differences can be accounted for by the underlying assumptions of the models.

When investigating efficiency -as well as economies of scale/scope- standard input-output analysis considers an indirect revenue function where firms are assumed to maximize revenue *either* for a given (fixed) vector of output prices and input quantities, varying output quantities, *or*, recently, (Berger , Humphrey and Pulley, 1996) for a given (fixed) vector of output quantities and input prices varying output prices. In the first case, the capacity of the firms to fix output prices is assumed to be non-existent, and in the second case firms have no capacity to expand output.

As it has been briefly described, there are many open issues in efficiency. In this paper we will concentrate on one which has mainly been addressed from a theoretical perspective. This controversial issue is the selection of inputs and outputs to be included in the estimation function. The existing alternatives for defining and approximating input and outputs are diverse.

The availability of data may be a key determining factor when choosing a given alternative. If reliable data on the number and size of deposits and loans is available, then there is no need to use a more imprecise measure such as monetary aggregates. Even if monetary aggregates are the only available data, it is possible to choose among stock and flow variables. The choice of stock values instead of flow variables (Resti, 1997) is justified by the argument that flow variables would be biased by market power because different banks charge different rates. Within this line of argument, it is assumed that the differences in rates have nothing to do with efficiency or input consumption. However, the differences in rates may be attributed to differences in the creation of value to customers. A broader branch network would be reflected in a higher volume of loans and deposits but also in higher prices due to the reduction in transaction costs to customers (Nelson, 1985). Therefore, we consider that, a bank with higher costs due to an extensive network would be penalized if stock variables are considered because it would be using more human and capital resources to obtain a lower quantity of loans and deposits.

There is some disagreement concerning the role of core deposits as an input or output Sealey and Lindley (1977). It is argued that they are an input to the production of loans or alternatively they are considered an output, because they involve the creation of added value (Berger and Humphrey, 1993) and customers are willing to bear an opportunity cost through lower interest rates on their deposits. Most papers adopt the second approach.

Mester (1996) includes financial capital as and input to the bank and adjust efficiency measures for the quality and riskiness of its output. Also accounting for risk, Clark (1996) tested a broader concept of cost, *economic cost*, which is constructed by adding production costs to the opportunity cost of capital. It is claimed that this new measure of cost should be considered as an improved measure of efficiency. It is argued that the assessment of the competitive viability of banking firms should consider the effects of resource allocation decisions on risk and return as well as on the explicit costs of production. Both efficiency measures, based on economic and production costs, are complete sets of inputs and outputs which are useful for obtaining a meaningful total measure of efficiency but the weighting of the incremental effect of the new input was not considered.

Little work has been done to weight and measure the relative importance of different inputs and outputs in business performance measures. The links between increments in productivity and increments in profits have been considered previously in the literature. In this line of work, profit change is decomposed into various effects and each effect is quantified. Recently, using a three-stage decomposition, Knox-Lovell and Grifell-Tatjé (1997) have obtained six components of profit change which are mutually exclusive and exhaustive. A single total productivity measure was estimated and linked to profit.

We propose that it may be interesting to consider partial measures of efficiency, each of which includes a reduced number of inputs and outputs. The objective will be to weight the relative importance of these partial measures and assess to what extent these measures are related to stock performance. Although partial productivity measures can vary in opposite directions, and it is not possible to unambiguously link any single partial productivity measure to a given business performance measure such as profit or stock performance, we propose alternative partial productivity measures which are simultaneously linked to stock performance in order to identify those combinations of inputs and outputs that are more closely related to business performance. This analysis cannot be achieved using the classic, complete measure of efficiency.

The rest of the paper is organized as follows. Section 2 presents and discusses the alternative cost functions and their definitions. Section 3 presents the model description, section 4 the computational experience and section 5 summarizes the paper and presents conclusions.

2. ALTERNATIVE MEASURES OF COSTS AND EFFICIENCY

When estimating efficiency, the usual alternative is to define only one set of inputs which are linked to only one set of outputs. Inputs and outputs are included and calculated based mainly on theoretical grounds. Defining partial measures of efficiency implies that a given bank will be more efficient than another (even though globally it may be less efficient) because a given input or output has not been considered, so that the ranking may be reversed when it is included. Having said this, if all relevant inputs and outputs are spread over the different partial measures of efficiency, it may be expected that the effect of a given input or output will be considered in its partial measure of efficiency.

We will consider the following measures: production costs, systematic risk, specific risk and branch network distribution. In table 1 there is a definition of all the inputs and outputs considered. The definitions proposed below are controversial and alternative definitions could have been considered. Firstly, when estimating production costs, we have selected flow variables instead of stock variables and we do not consider prices for inputs. Also, even though different approaches to measuring output have generally led to similar conclusions concerning the cost structures of financial firms (Mester, 1996), some inputs/outputs may not be standard. Although the necessity to include risk into efficiency measurement has been proposed previously (Clark, 1996; Mester, 1996). We do not follow the same specification when considering risks, so that our specification of risk measures is not backed by previous literature. Finally, the importance of the branch distribution network has been considered previously (Nelson, 1985) but the input formula and outputs selected for this measure are also non-standard. We have tried to justify on theoretical grounds why they were included and we will then test whether our model supported the initial choice. Further alternative partial efficiency measures may have to be define to compare results.

2.1. Production costs

Explicit production costs are defined to be the sum of the bank's operating and interest expenses. Those banking functions requiring significant expenditures on non-monetary inputs such as labor and physical capital to produce non-interest banking services are identified as outputs. Thus, outputs will be interest on loans, interests on deposits and net non-interest income. Net interbank funds are considered an input because banks with higher deposited funds at the interbank market are considered less efficient. We base our choice on the grounds that these banks are not able to find other assets yielding a higher (adjusted for risk) return or alternatively they are not efficient at selecting loan assets. Alternatively, it may be a sign of risk aversion, so that banks which are more risk averse prefer to invest higher volume of funds in the interbank market. If that were the case, we would take this effect into account in the following two partial measures. Net interbank funds are calculated subtracting funds deposited at the interbank market less funds borrowed at the same market. An adjustment is made to all the interbank figures to make the lower value, which is negative, equal to zero. General expenses include Personnel expenses plus administrative costs. Interest on loans and deposits include all interest, and also include interest on interbank funds. Net non-interest income is calculated subtracting non-interest income received less non-interest income paid.

2.2 Opportunity cost of capital with systematic risk

As defined in Clark (1996), a more risky collection of projects will require a higher expected return on the comparable financial securities and therefore, a higher opportunity cost of capital. The contribution of a security to the risk of a diversified portfolio depends upon the sensitivity of the security's returns to overall market movements. This sensitivity can be captured by the security's beta which is a measure of systematic (non-diversifiable) risk. Beta for the common stockholders in a bank can be estimated by regressing return data for the stock against a measure of market returns. It should also be taken into account that the interval over which returns are measured may affect beta estimates (Brailsford and Josev, 1997), hence, different betas estimates may be obtained. Since we are interesting in ranking banks by shareholders´ expected return on shares, according to the bank´s systematic risk, we would obtain the same results if we directly rank banks by beta. Notice also that $s_j^2 = b^2 s_m^2 + s_e^2$ where s_j^2 is the variance of bank j stock returns, b is the measure of systematic risk, s_m^2 is the variance of the market returns and s_e^2 is the variance of the error term. So that the same ranking can also be establish according to $b^2 s_m^2$. Thus, we will estimate this measure multiplying the variance of daily stock return by the coefficient of determination of the equation where we estimate beta.

2.3 Opportunity cost of capital with specific risk

Although ex-post measures of total risk, such as the standard deviation of the rate of return on equity/loan portfolio/assets, will overstate the risk incurred by individual investors, in the case of banks we may adopt the perspective of the theory of property rights (Barzel, 1989). Then any one who can be affected by the variations in value of an asset (bank) is in part its owner. The Regulator (Merton and Bodie, 1992) may be considered as a shareholder because the value of the deposit insurance fund is affected by the bankruptcy of banks, and this risk is difficult to diversify. Therefore the Regulator may impose restrictions on these banks and may try to control them on a more regular basis to prevent bankruptcy. This conduct may lower share value because of the signal sent to the market. Alternatively, it may be that specific circumstances of a banks such as a mergers or near bankruptcy status are not explained by systematic risk, hence specific risk will be high and may not influence negatively stock performance if in the case of a merger or a buy-out. We will estimate this measure multiplying the variance of daily stock return by ($1-R^2$) of the equation where we estimate beta.

2.4 Branch network distribution

The average cost curve is relatively flat, although there are some economies of scale at the branch level (Nelson,1985; Zardkoohi and Kolari, 1994). However the arrangement of the spatial distribution of branches may be important to customers. The location of branches relative to that of banking customers determines the extent of various transaction costs that add to the cost of consuming banking services (Nelson, 1985). Consumer transportation, time and information costs may be reduced through convenient branch location. Although user benefits cannot be directly observed, the reason that branches exists is that they are willing to pay for these savings in transaction costs (Berger et. al.,1996). If branch location were not an important dimension of the banking product, there would only be one-branch banking.

The geographic location of all branches of Spanish banks quoting on the Stock Exchange is considered in this paper. Notice that we will use the same outputs as in the production costs measure, which means that we could have had only one measure incorporating one extra input (branch distribution network) into production costs. However, we intended to measure the relevance of this particular input. These input will be computed by the following formula $[\sum_i (b_{ij} / b_i) \times h_i)] / TA_j$, where b_i is the total number of branches in province i (almost equivalent to a federal estate in the US) of Spain; b_{ij} is the number of branches of bank j in province i; h_i is the population of province i, and TA_j are the total assets of bank j. With this formula we expect to capture the spatial distribution efficiency of bank branches, adjusting for bank size dividing by total assets.

Table 1. Inputs and outputs considered

Efficiency Measures	**Inputs**	**Outputs**
Production costs (PC)	Net interbank funds General expenses	Interest on Loans Interest on Deposits Net non-interest income
Systematic Risk (OC_{sysr})	Variance of Bank Stock Return* R^2	
Specific Risk (OC_{spr})	Variance of Bank Stock Return*(1- R^2)	
Branch Distribution (BR)	Branch Distribution Measure	Interest on Loans Interest on Deposits Net non-interest income

2.5 Stock Performance

Stock performance may be expected to be the ultimate measure of efficiency. If bank stock prices reflect almost all the information about the past, present, and expected future performance of firms, then this measure would be the more reliable indicator of bank global efficiency. However, even if the choice of measures is correct, the previously described measures of efficiency may only be related to stock performance in the long run. Short term variations may not be explained by efficiency measures. In this case, individual bank effects may explain the majority of total variations in stock performance.

3. MODEL DESCRIPTION

We have defined four alternative measures of costs from which we derive four alternative, complementary measures of efficiency (see Table 1). We have estimated production costs and branch network distribution using Data Envelopment Analysis. Risk measures have been computed directly. Our objective is to establish the relationship between these four measures of efficiency and an additional unknown measure of efficiency, U, which accounts for all specific aspects of bank efficiency not considered in the previous four measures (it may include additional cost-efficiency measures, as well as customer satisfaction, other intangible assets of banks such as reputation and all other factors that affect bank performance and that are not accounted for in our 4 measures of efficiency). That is to say, our objective is to evaluate to what extent each efficiency measure is related to stock market performance through the following equation:

$$\alpha_1 PC + \alpha_2 OC_{sysr} + \alpha_3 OC_{spr} + \alpha_4 BR + \alpha_5 U + e = SP \quad (1)$$

where $\alpha_{1,...,}$ α_5 are the estimation coefficients and e is the error term, PC is the estimate of production cost efficiency using DEA, and OC_{sysr}, OC_{spr} BR are the efficiency estimates for opportunity cost with systematic risk, opportunity cost with specific risk and Branch network distribution using DEA. In this relationship, the efficiency of each bank in the U criterion is absolutely unknown. Finally, SP is Stock Performance.

3.1. *Collinearity treatment*

The alternative efficiency measures that have been defined may be correlated and hence there may be a problem of multicollinearity. Also, since we are employing DEA, an important part of the data may be figures close to the value 1, and thus there may also be another problem of multicollinearity.

When variables are collinear, individual effects cannot be isolated and the corresponding parameter magnitudes cannot be determined with the desired degree of precision. Griffiths et al. (1993, pp. 432-433), describing a collinearity problem associated with a production relationship explaining output as a function of various quantities of inputs in a cross section of firms, indicate that there are factors of production that are used in relatively fixed proportions and state: “It is clear, a priori, that any effort to measure the individual or separate effects (marginal products) of various mixes of inputs from these data will be difficult[...] Accurate forecasts of output may be possible for a particular ratio of inputs but not for various mixes of inputs.”

The consequences of collinear relationships among explanatory variables in a statistical model are that sampling variances, standard errors, and the covariances of the least squares estimators may be large. Thus, the information provided by the sample data about the unknown parameters is relatively imprecise. The problem is that the collinear variables do not provide enough information to estimate their separate effects, even though their total effect may indicate their importance in the relationship. Estimators may be sensitive to the addition or deletion of a few observations, or deletion of an apparently insignificant variable.

Collinearity is not a violation of any basic assumption of the linear statistical model. The least squares estimator is still the best linear unbiased estimate. The problem is that the best linear unbiased estimator may be too imprecise to yield useful results.

3.2 **Establishing the relationship among efficiency estimates**

In order to estimate the weight of each efficiency function in equation (1), that is to say, to what extent stock performance is associated with several measures of relative efficiency, the following procedure is implemented:

We will estimate the relationship between the four efficiency measures i=1,..,4 and SP, analyzing the relative strength of the banks b_j, j=1,...,b in this criterion f_i which is reflected in the ranking by this criterion.

Given equation (1), our first objective is to determine which vector U simultaneously best fits the equation conditioned to a low collinear relationship with respect to the other regressors. Considering the explanatory power of the first four criteria

$$\alpha_1 PC + \alpha_2 OC_{sysr} + \alpha_3 OC_{spr} + \alpha_4 BR + e' = SP \qquad (2)$$

where e′ is the error term of the regression. We are searching for a vector U $=\langle u_1,...,u_b \rangle$, $u_i \in [0,1]$ which can increase the explanatory power of equation (2), measured by means of the increase in the coefficient of determination, while keeping correlation with the previous four measures low.

Let $r^2_{1\ldots4|SP}$ be the coefficient of determination of equation (2) and $\hat{SP}$ the predicted SP using estimates of $\alpha_1, \ldots, \alpha_4$. If we call SP´ = SP - $\hat{SP}$, the maximum value $r^2_{U|SP'}$ could ever reach while being uncorrelated with other regressors is 1, which would be equivalent to explaining the remaining, $1 - r^2_{1\ldots4|SP}$, in equation (2).

Therefore, the objective is to find a vector U which simultaneously satisfies the following conditions: a) $r^2_{1\ldots4|U}$ is the closest to zero possible, and b) $r^2_{U|SP'}$ is the highest possible.

Vector U will express a part of the total variation in SP not explained by the previous four regressors while keeping correlation with other regressors as low as possible. The search for the best U which satisfies both conditions is implemented with the aid of the tabu search technique.

Once vector U is determined, the same methodology is employed to avoid collinearity and allow the isolation of the underlying relationships. However, this time the conditions will change slightly. For instance, when looking for the new first vector 1´, the objective will be to find a vector which simultaneously satisfies the following conditions: a) $r^2_{U,2,3,4|1'}$ is the closer to zero as possible, and b) $r^2_{U,2,3,4,1'|SP} \approx r^2_{1\ldots4,U|SP}$. Vector 1´ explains the same incremental variation as vector 1 and is least correlated with the other four vectors. Four additional artificial instrumental variables are generated by this process.

It should be noticed that there is no unique order of vector estimation. There are 4!=24 alternative estimation orders and in all cases the values for vectors PC´, $OC´_{sysr}$, $OC´_{spr}$, and BR´ will be computed. Among all the estimation orders, we shall choose that which leads to*min max*{ $r^2_{2'3'4'U|1'}$, $r^2_{1'3'4'U|2'}$, $r^2_{1'2'4'U|3'}$, , $r^2_{1'2'3'U|4'}$, $r^2_{1'2'3'4'|U}$ }.

Although instrumental variables are considered when regressors are correlated with the error term, we argue that we obtain an instrumental variable because it is uncorrelated with other regressors and it explains a part of the variation in SP which cannot be explained by the other independent variables. We show as an example the estimation of PC´, once vector U has been obtained in (1):

$$\alpha_1 PC' + \alpha_2 OC_{sysr} + \alpha_3 OC_{spr} + \alpha_4 BR + \alpha_5 U + e' = SP \qquad (3)$$

Now, equation (3) fulfills the role of equation (1) previously described. The vector obtained by this procedure would be that which can explain that part of SP not explained by the other variables but previously explained (after calculating vector U) in equation (1) and is simultaneously least correlated with them.

In summary, in this calculus process efficiency criteria have been estimated using a non-parametric deterministic technique, DEA, and subsequently a search heuristic, tabu search (TS), has been employed to search for artificial instrumental variables which avoid collinearity and permit the weighting of the underlying efficiency criteria. The artificial variables are then employed to estimate $\alpha_{1,}$ ...,α_5. It should be noticed that these artificial variables are only useful for estimating the weights of the primitive efficiency measures but are not efficiency measures themselves.

3.3 Techniques and methodologies

DEA is a nonlinear (non-convex) programming model which provides a scalar measure of the relative efficiency of each bank against its competitors and the weights of the input and output that characterizes a particular one by reference to a ranking of the observed results (Charnes, Cooper and Rhodes, 1978).

This measure is obtained as the maximum of a ratio of weighted outputs to weighted inputs subject to the condition that the similar ratios for every bank are less than or equal to unity. DEA assumes that there are no random variations, so that all deviations from the efficient frontier are considered as inefficiencies. See Berger, Hunter and Timme (1993), Cummins and Zi (1997) and Resti (1997) for a review of the literature and comparisons between econometric and mathematical programming approaches applied to financial intermediaries.

DEA may be used for analyzing technical efficiency, comparing inputs and outputs without taking into account the different economic value of each. Alternatively, it may be used with monetary inputs and outputs obtaining a global measure of efficiency, which is the approach followed in this study. It is possible to consider both prices and quantities in an Allocative DEA model (Resti, 1997), which would be useful for decomposing efficiency into complementary measures. However, this is not the aim of this paper. As mentioned above, we are concerned with evaluating the relative importance of the different inputs and outputs considered and our aim is not to decompose efficiency in other ways.

Tabu search has proven itself to be a useful optimization technique for solving large combinatorial optimization problems (Glover, 1989a,1989b; Glover and Laguna, 1996). Tabu search starts from a feasible solution and moves stepwise to a neighboring solution in an attempt to obtain an optimal or near-optimal solution after a number of moves. Neighboring solutions have to be constructed and evaluated before moving to the next solution. A move is then made to the best allowable solution in the neighborhood. However, the move may not necessarily improve the current value of objective function. This is a distinctive feature of tabu search, whereas other classic search techniques require each move to be an improving one.

Another important feature of tabu search is the use of a tabu list. This list contains a number of immediate previous moves which are not allowed at the current iteration. To a certain extent, the use of a tabu list alleviates the cycling problem since the search is prohibited from returning to any of the previous moves specified in the tabu list. The tabu list is updated by adding the new move and removing the oldest move from the list after each move. The use of tabu search has lead to excellent results in a wide variety of fields (Glover, 1990; Adenso-Díaz, 1992; Adenso-Díaz and Laguna, 1997). Specifically in finance, TS was implemented by Consiglio and Zenios (1998) to design callable bonds.

3.4 TS procedure for the estimations on U

As mentioned previously, the efficiency of each bank with respect to criterion U is unknown. To estimate these values, a procedure has been designed based on tabu search, the objective being to determine those efficiencies $u_1,...,u_b$ that best fit equation (1).

There are not many studies where tabu search is employed in the optimization of real functions (Glover, 1994; Fleurent et. al.; 1996), and these are almost always based on the use of gradients. With regards to the way real numbers are represented, a standard method is to transform the real number into base 2 and to store it as bits. This is the procedure followed in some TS applications of global optimization (Battiti and Tecchiolli, 1997; Woodruff and Zemel, 1993). In this way, the natural procedure used to define elements of the neighborhood of a given point is (Fleurent et. al., 1996) to randomly choose various components and to make $u_C' = u_C \pm 2^p$ where p is selected among values that will keep u_C' within a predefined boundary. Depending on the number of bits employed, different precision can be achieved.

In our case, considering the characteristics of the efficiency estimates, it was decided to approximate the value of the u_i coefficients to the thousandth. Therefore the space of solutions will be $\Omega = \{U=<u_1,...,u_b> : u_i \in \{0,1,...,1000\}\}$ and the objective function $f:\Omega \rightarrow [0,1]^2$ defined as $f(U) = < r^2_{U|SP'},\ r^2_{1...4|U} >$. Given that a regression with no intercept is estimated, $r^2_{U|SP'}$ and $r^2_{1...4|U}$ are calculated as $(\hat{y}'\hat{y} / y'y)$ where y is the dependent variable and $\hat{y}$ the estimate of y.

The search is directed through a set of vectors $\vec{m} \in \{-1,0,+1\}^b$ which define the neighborhood of the actual solution $N(<u_1,...,u_b>) = \{<u_1',..., u_b'> : u_i' = u_i + m_i\varepsilon\}$ where parameter ε indicates the step increase. This parameter is variable throughout the search depending on whether we want to favor diversification or intensification.

It should be noticed that given a vector U, there exist infinite vectors kU, $k \in \Re$, $ku_i \in [0,1]$, with the same f(U). To overcome this fact, the selected vector is normalized in each iteration, so that $\max\{u_i\}=1$.

Since card {N(U)} = 3^b, it is not possible to exhaustively evaluate the whole neighborhood in each iteration. For this reason, a number of vectors $\vec{m}$ is generated in each iteration, the one that obtains the best value according to f(U´) being selected as the new $U' \in N(U)$. The generation of vectors is random following a distribution function F_i which considers for each component i the values m_i which appeared most in previously accepted movements. Periodically, the search is diversified by making any value m_i equally probable. To avoid cycling for a predefined number of iterations (tabu tenure), a movement $<m_1,...,m_b>$ is considered tabu if the movement $<-m_1,...,-m_b>$ has been previously accepted (except if the aspiration level is exceeded). Figure 1 presents a pseudocode for this algorithm.

------------------------ Figure 1

4. COMPUTATIONAL EXPERIENCE

The data to estimate our four partial measures of efficiency was obtained from files provided by Madrid Stock Exchange (daily market quotes) and AEB, Spanish Banking Association (annual income and balance sheet data). In addition, data for the location of bank branches -by difference the more time consuming measure to obtain- was collected from several sources including two Central Bank Bulletins, the Spanish National Institute of Statistics and Spanish Chambers of Commerce.

One important shortcoming of the data is the number of Banks quoting on the Stock Exchange. It is only possible to obtain full sets of data for the period 1993-1995 for only twenty three banks out of a total of twenty eight banks currently quoting on the Madrid Stock Exchange. Below we present results for year 1994 (Table 2).

Due to time constraints data for 1993 and 1995 are not included in the current version of this paper.

Table 2 - Efficiency measures for all the banks quoting on the stock exchange in 1994

Banks	PC	OC_{sysr}	OC_{spr}	BR	SP
BANESTO	0.777	0.969	1.000	0.269	1.000
CASTILLA	0.896	0.002	0.077	0.017	0.698
ZARAGOZANO	0.633	0.151	0.088	0.024	0.351
BILBAO-VIZCAYA	0.998	0.742	0.021	1.000	0.340
EXTERIOR	1.000	0.040	0.002	0.882	0.322
MAPFRE	0.510	0.000	0.002	0.003	0.319
GALICIA	0.893	0.013	0.009	0.019	0.313
POPULAR	1.000	0.536	0.020	0.159	0.309
BALEAR	0.680	0.031	0.052	0.010	0.307
VALENCIA	0.565	0.275	0.057	0.012	0.286
ALICANTE	0.795	0.018	0.001	0.147	0.282
HERRERO	0.645	0.312	0.056	0.014	0.274
ATLANTICO	0.696	0.026	0.005	0.026	0.274
HISPANO	0.952	0.735	0.027	0.789	0.271
SIMEON	0.659	0.010	0.002	0.006	0.270
ANDALUCIA	0.978	0.138	0.021	0.130	0.264

BANKINTER	1.000	0.621	0.031	0.008	0.244
BNP	0.588	0.001	0.158	0.038	0.240
VASCONIA	0.994	0.026	0.016	0.154	0.236
PASTOR	0.927	0.090	0.025	0.019	0.221
SANTANDER	1.000	1.000	0.047	0.908	0.192
VITORIA	0.694	0.008	0.026	0.015	0.087
GUIPUZCUANO	0.712	0.034	0.028	0.039	0.000

Estimates for production costs and branch distribution were obtained using DEA. Risk measures, systematic and specific risk, were calculated adjusting for dividends and share issues. Vectors were normalized so that $\max\{u_i\}=1$. That is to say, figures were divided by the highest value in the list to obtain a ranking beginning in 1. Stock performance was calculated for each bank adding daily returns on stock for the whole year period. This measure was considered to be better than directly calculating a point increase with data from the first day and the last day of the year.

In order to obtain a more rapid convergence in the search of the vectors by the TS procedure, a number of experiments were carried out which permitted a tuning of the defined parameters in our algorithm. To be more exact, a tabu tenure of 30 movements was selected, increasing the importance of the aspiration level as the tabu tenure increased.

In the election of the initial solution, the speed with which a solution is found with a low correlation coefficient with respect to the other four criteria has been taken into account, and for this reason, the search departs from a $U=<u_1,...,u_b>$ where all u_i are equal to zero except one, $u_{i_0}=1$. Then, the b vectors which fulfill these conditions are generated and the initial solution with the lowest $r^2_{1\ldots4|U}$ is chosen.

Table 3 - *Coefficients of determination for the different alternative orders*

Order	$r^2_{2'3'4'U\|1'}$	$r^2_{1'3'4'U\|2'}$	$r^2_{1'2'4'U\|3'}$	$r^2_{1'2'3'U\|4'}$	$r^2_{1'2'3'4'\|U}$	***Max.***
<1234>	0.0118237	0.0077973	0.0115265	0.0088709	0.0026588	0 .011824
<1243>	0.0101120	0.0048850	0.0092498	0.0089324	0.0016908	0 .010112
<1324>	0.0285143	0.0556761	0.0616528	0.0093725	0.0022669	0 .061653
<1342>	0.0320962	0.0396149	0.0512548	0.0182378	0.0013469	0 .051255
<1423>	0.0110484	0.0082449	0.0096394	0.0062551	0.0016836	0 .011048
<1432>	0.0366402	0.0399914	0.0658882	0.0118295	0.0012474	0 .065888
<2134>	0.0063747	0.0071945	0.0037640	0.0099811	0.0011337	0 .009981
<2143>	0.0050546	0.0064283	0.0099852	0.0080225	0.0016612	0 .009985
<2314>	0.0101558	0.0103661	0.0095684	0.0099000	0.0007880	0 .010366
<2341>	0.0090168	0.0115415	0.0113327	0.0019152	0.0013181	0 .011542
<2413>	0.0108462	0.0062478	0.0097435	0.0033916	0.0008258	0 .010846
<2431>	0.0089917	0.0077134	0.0053875	0.0046581	0.0022678	0 .008992
<3124>	0.0088059	0.0052022	0.0071620	0.0099310	0.0018998	0 .009931
<3142>	0.0066021	0.0099994	0.0073805	0.0085493	0.0023079	0 .009999
<3214>	0.0083161	0.0569978	0.0500049	0.0095718	0.0100893	0 .056998
<3241>	0.0099422	0.0613154	0.0537670	0.0080850	0.0092578	0 .061315
<3412>	0.0162674	0.0199919	0.0155942	0.0092785	0.0010661	0 .019992
<3421>	0.0074524	0.0348187	0.0388976	0.0089116	0.0005278	0 .038898
<4123>	0.0140671	0.0079662	0.0099683	0.0015591	0.0011455	0 .014067

<4132>	0.0390516	0.0399452	0.0667609	0.0001774	0.0017548	0 .066761
<4213>	0.0097286	0.0052971	0.0088910	0.0010092	0.0006515	0 .009729
<4231>	0.0099178	0.0069272	0.0058998	0.0015715	0.0020631	0 .009918
<4312>	0.0115850	0.0095299	0.0019128	0.0024198	0.0014829	0 .011585
<4321>	0.0025218	0.0016715	0.0033141	0.0001422	0.0005846	**0 .003314**

In order not to excessively slow down the search process while allowing for a significant exploration of the neighborhood of N(U), the number of elements in the neighborhood examined is 100. It departs from an initial value of $\varepsilon=25$, reducing this value as the search goes on with the aim of obtaining a better adjustment for elements u_i. After 50 (*constant1* in Figure1) iterations with a given ε and no improvements, ε goes back to 25, and in addition we make equally probable to select any m_i. The search finishes after 500 (*constant2*) iterations without improvement. With this schedule, it is possible to estimate the vectors in an average time of 725 seconds in a Pentium 120Mhz Processor.

After running for the data in table 2 the procedure previously explained (see table 3 for a complete description of the coefficients of determination obtained for the different orders), we have obtained the new vectors that can be seen in table 4 below for order <4321> which was the best scored according to our criterion. These new vectors explain exactly the same information as the original efficiency vectors (plus the U vector) but with a minimum correlation among them.

When estimating artificial variables, several vectors U could have been considered to increment the coefficient of determination. However, for the data considered, an additional vector U increased by a marginally insignificant amount the explanatory power of the equation.

It should be noticed that in table 4 single values are meaningless in determining individual efficiency since they are just artificial variables employed to calculate α_i estimates.

Table 4 - Final vectors obtained using the TS procedure for estimation order <4321>.

Banks	PC´	OC´sysr	OC´spr	BR´	U	SP
BANESTO	0.143	0.083	0.647	0.000	0.019	1.000
CASTILLA	0.007	0.000	1.000	0.000	0.000	0.698
ZARAGOZANO	0.008	0.798	0.000	0.000	0.000	0.351
BILBAO-VIZCAYA	0.857	0.001	0.000	0.000	0.061	0.340
EXTERIOR	0.505	0.000	0.000	0.000	0.000	0.322
MAPFRE	0.001	0.000	0.002	0.006	1.000	0.319
GALICIA	1.000	0.005	0.002	0.000	0.000	0.313
POPULAR	1.000	0.007	0.000	0.000	0.000	0.309
BALEAR	0.025	0.001	0.193	0.000	0.000	0.307
VALENCIA	0.002	0.007	0.007	1.000	0.000	0.286
ALICANTE	1.000	0.000	0.000	0.000	0.000	0.282
HERRERO	0.948	0.000	0.058	0.000	0.000	0.274
ATLANTICO	1.000	0.000	0.002	0.000	0.000	0.274
HISPANO	0.333	0.007	0.002	0.000	0.000	0.271
SIMEON	0.999	0.004	0.000	0.000	0.000	0.270
ANDALUCIA	1.000	0.000	0.000	0.000	0.000	0.264
BANKINTER	0.753	0.000	0.000	0.000	0.000	0.244
BNP	0.035	1.000	0.003	0.000	0.000	0.240

VASCONIA	0.637	0.000	0.000	0.000	0.000	0.236
PASTOR	0.879	0.000	0.000	0.000	0.000	0.221
SANTANDER	0.749	0.000	0.000	0.000	0.014	0.192
VITORIA	0.254	0.000	0.003	0.000	0.000	0.087
GUIPUZCUANO	0.118	0.007	0.008	0.139	0.000	0.000

Finally, the regression of the independent variables against stock performance for the selected order gave the following $\alpha_{1,\ldots,}$ α_5 estimates:

$$0.305\ PC' + 0.325\ OC'_{sysr} + 0.925\ OC'_{spr} + 0.265\ BR' + 0.324\ U = SP$$

At this stage the correlation of explanatory variables is below 0.4% in all cases. In addition, after these steps, it is possible to evaluate the weight of each of the selected criteria in explaining bank stock performance. It can be observed that the more influential criterion is the specific risk of banks implying that variations in stock performance can be attributed to particular factors affecting bank performance.

Should also be noticed that the alfa values obtained for the different permutations are not very different among them, as can be seen in table 5, with variances very low in all cases.

Table 5 - Alfas descriptive values for all the orders

	OP	Ocsys	Ocspr	BR	U
Mean	0.34706	0.30736	0.83028	0.24543	0.31274
Variance	0.00249	0.00335	0.03683	0.01100	0.00016
minimum	0.25933	0.17035	0.38270	-0.06889	0.28627
Maximum	0.43333	0.42797	1.01483	0.39527	0.32640

5. CONCLUSIONS

In this paper we have sought to establish a link between stock performance and different measures of partial efficiency: production costs, systematic risk, specific risk and branch network distribution. We estimate production cost and branch network distribution with DEA and we also incorporate two risk measures in the analysis which are systematic risk and specific risk calculated from daily stock return data. We use a TS algorithm to compute the relative importance of each of the cost functions and define an additional cost function which can be attributed to other cost differences not accounted for in the previous four definitions.

The main finding of this article is the development of an innovative tool to generate artificial instrumental variables which are uncorrelated among them and explain the same variations as the original measures. This procedure was used to evaluate the influence of alternative partial efficiency measures obtaining that the most influential variable is specific risk of banks in determining stock performance. Further research should consider alternative efficiency definitions, and alternative efficiency estimation methodologies as input for the TS procedure.

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```
Fi(-1) = Fi(0) = Fi(+1)= 1/3    ∀i = 1,..,b ;
Tabu_list= ∅ ;
U^act :=Choose_initial_solution ;
U^best := U^act ;

REPEAT

        Iteration := Iteration+1 ;
        IF iterations_without_improvement > constant1 THEN {reset_eps; reset_Fi};
              ELSE IF iterations_without_improvement > constant3 THEN eps:=eps-delta;
        FOR card_neigh points DO {
            Generate m→ according to Fi ;
            Ui′:= U^act + mi * eps ;
            Choose U′ such that m→ is not tabu and best value is obtained;
                                        };

        Tabu_list:= Tabu_list ∪ (-m→);
        U^act:= Normalize (U′);
        Update Fi according to m→ ;
        IF U^act is the best one THEN U^best := U^act ;

UNTIL number_iterations_without_improvements > constant2;


Write (U^best);
```

Figure 1. *Pseudocode for the algorithm*