Econometric Techniques in Firm Level Efficiency Analysis: Ideas on Applications to Banking

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In attempting to write about the uses of econometric approaches to measuring firm, or in this case, bank efficiency, one is immediately inclined to refer the interested researcher to a number of high-quality, survey articles recently written on this topic. For example, see Bauer; Lovell and Schmidt; Forsund, Lovell and Schmidt, for consideration of technical aspects of econometric estimation with frontier functions, and Evanoff and Israilevich for an overview of issues in studying efficiency in banking as well as a review of empirical banking studies.

The above literature is essentially concerned with the following issues: can we measure the extent to which firms are allocatively efficient (AE), technically efficient (TE) and scale efficient (SE)? Forsund et al. concisely define these terms. Empirical banking studies have also focused on the existence of economies of scope. A number of such studies are catalogued in Evanoff and Israilevich. For example, see Benston, Hanweck, and Humphrey, or Gilligan, Smirlock and Marshall.

In measuring efficiency of firms there is a non-parametric alternative to frontier functions called data envelopment analysis (DEA) as reviewed in Banker et al. and applied in Neff et al. This technique uses linear programming to envelop the observed points and compute the efficiency for a firm compared with other firms in a sample. In a Monte Carlo comparison of DEA with a single equation frontier approach using a translog function, Banker et al. show the DEA method to be superior to the econometric approach. It should be observed, though, that in this comparison the econometric approach is not the most precise that could be used.[1] Nonetheless, the DEA approach is certainly worth consideration and has a respectable place in the methods. In an applied study to banking Ferrier and Lovell apply both a stochastic frontier technique and a DEA approach and find the two different approaches give somewhat different results about efficiency.

In this paper we will consider some of the basic methodology of the econometric approach and then some variants that seem to have been overlooked in the real world problem of measuring economic efficiency. First, some basic definitions are given with respect to measures of efficiency and the customary econometric approaches. Then we shall consider how a bank should be modelled conceptually since there is some debate about this in the literature, selection of appropriate approximating form, implications of using static forms for the bank in what clearly is a dynamic optimization problem, homogeneity over time and cross section, and implications of the firm's objective function on estimation and efficiency analysis.

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Definitions and Some Basic Econometric Issues

Following Forsund et al. a firm is said to be technically efficient if it gets the maximum output from a given set of inputs that is possible for the firm as given by its technology. Letting $\underline{x}$ be a vector of inputs and y the output, then technical efficiency is defined as $y^0 = f(\underline{x}^0)$. Any $y < y^0$ indicates a technically inefficient firm. Allocative efficiency is said to obtain if the ratio of the marginal products of each input is equal to the ratio of the prices of these inputs, assuming that the firm is in a competitive industry with respect to both inputs and outputs. A firm that is both AE and TE is not necessarily totally, economically efficient it there are scale effects. The efficient firm must also be producing at that level where the output price equals the marginal cost of output. Forsund et al. further summarize the various kinds of efficiency by noting that a firm is efficient if the observed inputs and output satisfy the profit function. A firm whose costs are greater than those given by its cost function could be both inefficient allocatively or technically.

The above definitions follow the Farrell approach with just one output. For multiple outputs more encompassing definitions are given in Lovell and Schmidt. In their treatment efficiency is defined in terms of the dual functions to the production technology, namely the cost function, $C(\underline{w},\underline{y})$, where $\underline{w}$ is the vector of input prices and $\underline{y}$ is the vector of outputs, the revenue function, $R(\underline{x},\underline{p})$, where $\underline{p}$ is vector of the price of outputs, and the profit function, $\pi(\underline{w},\underline{p})$. A firm is said to be AE, TE, and SE if the observed profits are equal to that given by $\pi(.)$ for the observed input and output prices. Allocative and technical efficiencies are defined slightly differently with respect to the revenue and cost functions. Akridge gives succinct definitions of generalized Farrell measures of efficiency using a cost function. Akridge also defines two ways of measuring the technical and cost efficiencies of using particular inputs, other inputs held constant.

In addition to measuring efficiency, there is usually interest in measuring economies or diseconomies from multiple outputs. The traditional measure, and certainly the most popular, is that of economies of scope as defined by Panzer and Willig. Economies of scope are said to exist if the cost of producing observed output levels jointly is less than the cost of producing each output individually. Leathers further discusses the existence of economies of scope in the short run that may arise due to a fixed, allocable input. The concepts of economies of scope and scale can be measured on an output specific basis as discussed in Tripp or Mester.

It should be pointed out that economies of scope are difficult to measure using a translog form for the cost function. This problem arises because in computing the measure of economies of scope it is necessary to have all of the outputs at a zero level and that necessitates taking the logarithm of zero. This problem could be attacked using a Box-Cox transformation (see Cebenoyan) in estimating the cost function, but the simpler approach is to set output to some negligible level and consider this as a zero output. This is the approach taken in Mester and a study by Kim. Since cost complementarities are sufficient for economies of scope, an alternative test for the existence of economies of scope can be

conducted on the second derivatives of the cost function although Mester urges some caution about the actual point of approximation.

In estimating economies of scale and scope there is typically some concern about the standard errors of the point estimates. In using a translog cost function, the standard errors of the measures of economies of scale and scope have only recently become standard measures. Obtaining the standard error of economies of scale (global) is routine. Asymptotic approximations have been used, for example, in Mester. A more reliable approach to estimating such standard errors as well as those for economies of scope, is probably a bootstrapping method as demonstrated in Eakin, McMillen, and Buono.

In reviewing the existing literature on measuring firm efficiency, little appears to be said about standard errors of the various measures of firm inefficiency. Bootstrapping (Efron) is not a particularly attractive option for estimating realized error terms in the case of frontier functions because the actual values of the error terms cannot be easily shifted around to other observations as is typically required by bootstrapping.[2] Nonetheless, the need for determining if observed differences in efficiencies can in any way be considered statistically significant is deserving of some attention as a general methodological issue in efficiency studies. The major difficulties in constructing such tests is that a given residual cannot be estimated in the conventional sense but predictions of actual realizations can be made and approximate standard errors computed for the purposes of inference. This is an area deserving further attention perhaps along the lines of the least significance difference literature as in Snedecor and Cochran. Berger and Humphrey recognize the implausibility of estimating an exact frontier edge, select observations of an efficient group and estimate a "thick frontier".

The Journal of Econometrics has published two special issues on estimating frontier functions (vol. 13, May 1980 and vol. 46, Oct./Nov. 1990) investigating many econometric difficulties associated with the unusual properties ascribed to the error terms. It is fascinating that in estimating a production function, little attention that the author can see has been paid to the simultaneity problems inherent in estimating a production function assuming input levels are determined endogenously. This, of course, is one of the advantages of dual methods over primal methods. In estimating cost functions the assumption must be made that the outputs are fixed and this seems hardly the most realistic assumption about current banking behavior. It would seem that estimating multiproduct profit functions is preferable to either the primal approach of a production function or the dual cost function.

Modelling the Bank

There appear to be two ways for modelling banks in terms of transformation functions of inputs into outputs. The first is labelled the production approach by Ferrier and Lovell. In the production approach loans and deposit accounts are viewed as the outputs using labor, capital and other inputs to produce them. The various types of deposit accounts and loans can be subdivided as appropriate for a multiple output approach. In their study Ferrier and

Lovell categorize outputs into time and demand deposits; and commercial, real estate, and installment loans. The corresponding inputs are total number of employees, occupancy costs and expenditure on furniture and equipment, and costs of materials.

The second method is the intermediation approach. Banks are viewed as institutions which attract deposits and then intermediate them into loans. In this approach the dollar volume of loans and deposits is viewed as the output, and operating costs plus the interest on deposits are the costs of production. Mester notes that deposits are not always regarded as outputs and in her study deposits are viewed as an input. Mester cites a number of studies using various approaches. Sealey and Lindley give a justification for viewing deposits as inputs as opposed to outputs. In any event there does not appear to be unanimity on how the intermediation approach should be applied.

A more major question is which of the two general approaches, production or intermediation, should be used? Ferrier and Lovell argue for resolving this issue on the basis of the questions to be investigated by the empirical analysis. Their resolution is that the production approach is appropriate for studying the cost efficiency of banks since only the operating costs are considered. In the intermediation approach all of the costs are being considered so that this latter approach is more applicable to analyzing the "economic viability of banks" (Ferrier and Lovell, p. 231).

This question might also be partially resolved by considering the type of function being estimated. In a dual approach a profit function would be more properly estimated using an intermediation approach in which costs should include interest on deposits. A cost function could be used with either approach, but as mentioned earlier, there is the troubling aspect that outputs are being assumed to be fixed exogenously when they clearly are not. Using a primal approach requires resolving the even bigger problem of aggregating different outputs so that the question of intermediation or a production approach is relegated to that of a minor concern. If one takes Leamer's extended bounds analysis approach, an argument can be made that both the intermediation approach and production approach should be taken. If the results and implications are substantially different, this might be taken that inferences from either approach are fragile and therefore, suspect. Likewise, a DEA approach could be applied to both the intermediation and production methods to measure the robustness of the results.

Selecting the Approximating Form

In undertaking an econometric efficiency study, regardless of whether a production or intermediation model, or primal or dual approach, or frontier or average function, are to be used, the researcher must confront the issue of what functional form to select. As numerous authors of econometrics textbooks have lamented, economic theory does little to guide the empirical researcher in the quest for the correct functional form or appropriate specification of the error distribution. Indeed, it is this lack of knowledge about the correct functional form that leads to one of the justifications of the random, usually additive, error term (see

Darnell and Evans). While there are a number of flexible functional forms, there is no doubt that the translog is probably the favorite, particularly among agricultural economists. As McCloskey pointed out in analyzing the August 1989 issue of the American Journal of Agricultural Economics, many of the articles therein utilized the translog. Much research has been undertaken to judge the usefulness of the various approximating forms, see for example Guilkey, Lovell and Sickles, or Dixon, Garcia and Anderson. Indeed, the AJAE has been active in evaluating flexible functional forms. Driscoll and Boisvert exam the reliability of the translog under various stochastic assumptions and Driscoll, McGuirk and Alwang investigate the conditions under which flexible forms will be flexible.

It should also be noted that agricultural economists are not alone in their admiration or, at least, readiness to utilize the translog. Mester; Ferrier and Lovell, Banker et al. use the translog model in their studies. This is no doubt due to the linear-in-parameters nature of the translog model, but the generalized Leontief and quadratic flexible forms also share this convenient characteristic.

A general conclusion about the translog is that it is yet to be definitively surpassed, although its performance can be far from the mark. This may be true for other forms as well. It is interesting that in a comparison of the DEA approach with the econometric approach conducted by Banker et al., the translog function was found to be inferior to the nonparametric approach. While such a finding is certainly significant, recall that the underlying technology was not constant over all observations so that the second order approximation represented by the translog was not estimating one, underlying technology. Also, the comparison was with a single output and, in the banking studies envisioned, multiproduct approaches are likely to be utilized since the results of such studies are much more informative.

What one would really like to know about the translog and comparisons with DEA or other functional forms, is how well they compare with multiple outputs. To my knowledge all of the Monte Carlo work comparing the flexible forms has been with a single output technology. If concern is with multiple output technologies, then much of the comparison work and validity of the dual, flexible forms needs to be established in terms of an underlying multiple output technology. While nobody seems to have come up with an explicit form for a multiple output technology, one could envision getting multiple outputs from a mathematical programming model and then estimating the corresponding dual functions to see how well they replicate the technology. In such an experiment, it would probably be best to have nonlinear technology and some shared fixed inputs to give technologies more similar to those given by current neoclassical technologies in say, Hanoch.

It is easy to say that the correct functional form should be chosen for estimating the primal or dual function. Alston and Chalfant show that using the incorrect functional form can lead to the conclusion that structural change exists when, in fact, only the incorrect form has been used. This is hardly surprising and explains why the Hendry and Richard approach to econometrics, consisting of extensive model testing, has gained in popularity.

About all one can really do is select alternative forms and see which one appears to fit the data best in the sense of customary goodness-of-fit (R-square, adjusted R-square, etc.) as well as consistency with the assumptions of the underlying statistical model. In such a situation it is to be expected that no, one functional form will surpass all others. In this case it is to be hoped that the results of the varying functional forms that seem nearly equivalent on statistical grounds will give roughly the same results. If they do not, we are again faced with a fragile inference and non-conclusive results.

In model specification one would also like to be able to identify the correct distribution for the error term, particularly in frontier models. Although my review of the econometric frontier literature was not exhaustive, there does not appear to be much guidance on testing the assumed error distribution in any formal way. This may be due partially to the complexity of obtaining the ML estimates even for the few distributions now in use. One would like to see some empirical guidance on this question, particularly for small samples.

Further Specification Problems

It is to be expected that a given functional form will not necessarily fit all the firms in a population. This is not a trivial issue. Error terms in econometric models are a composite of every thing not modelled explicitly in the regression function. If there is some variation in the appropriate functional from among banks in the sample, the error term is going to incorporate this. Assume a frontier model is being estimated where the error term is composed of two error terms: one for random error and the other with a one-sided distribution to reflect inefficiency. It would be convenient to think this would be modelled by the error term that represents non-technical error and not that part of the composed error that accounts for not being technically efficient. There is no reason to believe this would be true. If a firm has a different technology, then the misspecification bias could likely be partially accounted for by the error term that is supposed to represent pure technical efficiency.

Bauer discusses estimating a firm-specific inefficiency parameter in a panel data context by letting the intercept vary among firms. Then no particular assumptions have to made about the disturbances representing inefficiency. However, this assumes that a firm's inefficiency is constant over time. As Bauer points out, this assumption becomes less tenable as more time periods are observed. This difference in intercept terms could also reflect a mean specification error.

An advantage of the cross sectional approach is it then becomes easier to test for homogeneity of slope coefficients across firms using standard methods such as the F test. Such methods do not strictly apply when the sample is purely cross sectional. In order to test for slope homogeneity, one could make informed (based on non-sample priors) assumptions about which firms should be grouped together. For example, n_1 observations can be put into one sample and n_2 can be put into another sample according to some rule such as bank size. Then both samples can be estimated by a maximum likelihood frontier estimator and a likelihood ratio statistic could be used to test the assumption of coefficient homogene-

ity. An alternative approach applicable to relatively small samples would be to estimate the parameters n times omitting each of the observations once. Any observation whose omission causes a large variation in the estimate slope coefficients would then be regarded as an outlier.

The lack of homogeneity of coefficients is, of course, simply one method of overall specification testing. Because of the complexity in translating a theoretical model of a firm into an estimable model, should there not be some specification testing? That is, tests such as Ramsey's RESET or a Hausman test would seem appropriate. In my limited review of applications of frontier models, so much time is spent dealing with the error terms and appropriate estimation given their distribution, little time seems to be devoted to these larger questions.

In all of the banking efficiency studies reviewed, none of them address dynamics. This is hardly a glaring deficiency since many of the duality studies and firm efficiency studies also view firms in a static context. The customary approach in static studies of efficiency is to have quasi-fixed factors and then assume the firm optimizes with respect to some objective function. This is fine if that is indeed what the firm is doing, but it is likely a substantial simplification of the underlying process. The possibility of using dynamic models in a dual context has been explored and applied by Lopez. His study is not applied to banking but nonetheless assumes an intertemporal objective function maximizing discounted profits over an infinite horizon. In his study Lopez takes a duality approach and estimates a profit function. It should be noted, though, that dynamic duality is more complex than static. Taylor illustrates instances in which dynamic duality would not be applicable. Nonetheless, in doing a banking study it would not be incumbent upon the researcher to undertake a duality approach. Much of the frontier estimation technology undertakes a primal approach. Nonetheless, simultaneity problems may still remain with primal estimation.

Behavioral Assumptions and Measuring Efficiency

In work to date using frontier approaches, little attention is devoted to analyzing how firms generate the observations. It seems the maintained hypothesis is each firm maximizes deterministic profits assuming the firm knows its production function and that all prices are known. The failure of the firm to conform exactly to these assumptions gives rise to the justification of the various error terms. How this error term is viewed by the firm can have an impact on efficiency measures.

Consider a fairly simple case where the firm knows prices of inputs ($\underline{w}$) and the price of its only output, p. The only randomness the entrepreneur faces is from the production function. Given the selected input levels, the resulting output level is random. Suppose two inputs are used to produce one output and the entrepreneur acts as if he maximizes deterministic profit. If the error term on the production function is additive, then maximizing expected profit is equivalent to maximizing deterministic profit where the random error term is equal to its mean of zero in computing the optimal output levels.

If the error term on the production function is not additive but multiplicative as in a Cobb-Douglas or translog, then if the firm maximizes expected profit, the necessary conditions for an optimum are different from those of maximizing deterministic profits as discussed in Zellner, Kmenta and Dreze. The optimal levels of the inputs will also vary. To see this, assume a two input, Cobb-Douglas production function of the form

$$y = Ax_1^{\alpha} x_2^{\beta} \epsilon$$

where ϵ is some stochastic error term bounded between one and zero to reflect a firm's technical inefficiency. The bound of one represents maximum efficiency, i.e., the producer is at the frontier. (Clearly, ϵ could be a composite error as in Lovell and Schmidt. However, for the purposes of the point to be made here, it is sufficient that the expectation of the error term not be one when it is in the model in a multiplicative form.) Let the mean of ϵ be μ. The firm wishes to maximize expected profit or

$$E(\pi) = pax_1^{\alpha} x_2^{\beta} \mu - w_1x_1 - w_2x_2.$$

Working though the necessary conditions gives the derived demands as

$$x_1^* = \left(\frac{\alpha}{w_1}\right)^{(1-\beta)/\gamma}\left(\frac{\beta}{w_2}\right)^{\beta/\gamma}(Ap\mu)^{1/\gamma} \tag{1}$$

where $\gamma = 1-\alpha-\beta$ and a similar expression obtains for x_2^*.

It is clear from (1) that the expected profit maximizing level of x_1^* (*and* x_2^*) is less than if output were deterministic for $\mu < 1$. However, in an analysis of allocative efficiency, an entrepreneur would be deemed inefficient if the level of x_1 were different from x_1^* under the assumption that μ is equal to one. The problem arising here of producer objectives is not much different from that faced when estimating a dual function. That is, what set of error assumptions are appropriate for the dual function, i.e., what set of distributional assumptions are appropriate for the error terms in estimating an econometric model?

In testing for firm level efficiency it seems that if profit maximization is assumed, then maximizing <u>expected</u> profit should be assumed. It also seems reasonable that the producer assume the error term be bounded as assumed in the frontier model or a composed error of random behavior and efficiency. Thus, in developing the criteria to measure allocative efficiency or scale efficiency, the criteria should incorporate the moments of the estimated distribution. It would be convenient if there were an efficient econometric test for determining if the producer were maximizing expected profit or deterministic profit. Something along the lines of Pope and Just to estimate the structure of risk preferences would be helpful. One ad hoc approach would be to estimate the parameters and then determine whether the observed input levels were closer to those for expected profit maximizers or deterministic profit maximizers.

A small experiment with a one input Cobb-Douglas using data from expected profit maximizers and deterministic maximizers was performed to see if the parameter estimates would differ. The error term was composed of a log normal random error and exponential random variable for technical inefficiency. Input levels varied proportionally between expected and deterministic maximizers. Identical errors were used for both experiments. The slope coefficients were identical and constant term estimates varied negligibly. For a sample size of 100 the expected profit maximizer had higher mean profits. Other than those differences, results were identical. However, an allocative efficiency analysis would have given different results depending on whether it was assumed the firms were maximizing expected profit or deterministic profit. Thus behavioral assumptions do matter and should be investigated to the extent possible.

Estimating Dual Functions

As argued earlier, much of the analysis performed with frontier functions or estimates of dual cost or profit functions is predicated on the underlying technology being well-behaved and producers maximizing profit or minimizing cost. In this section we investigate the reliability of dual profit functions when producers are maximizing expected profit as compared with maximizing expected utility. For the latter case two different utility functions are used. In the first case producers are assumed to be maximizing the natural log of wealth where wealth is defined as the level of expected profits for one period plus the net revenues from the current period of production. The second utility function is the negative exponential with a risk aversion coefficient of 3.0. This level was chosen so that the optimal levels of inputs for expected utility maximization would differ noticeably from the profit maximizing levels. In general input levels varied by two percent down to twenty percent for at least one input. While 3.0 might seem a high level of risk aversion, one period's profits usually lay between zero and one. Raskin and Cochran show that the marginal utility of wealth varies with the scale of the returns.

A Monte Carlo approach is used. Essentially the same procedure used in Dixon, Garcia and Anderson is used in terms of the technology and summary statistics. Three technologies are hypothesized using a generalized CES production function of the form:

(2) $y = (.3x_1^{-\rho_1} + .3x_2^{-\rho_2} + .4x_3^{-\rho_3})^{-(1/\rho)}$

The parameters ρ_1, ρ_2, ρ_3, and ρ are parameters that vary with the technology. In technology 1 all three pairs of inputs have mean Allen-Uzawa partial elasticities of substitutions (AES) greater than one, implying easy substitution. In technology two, input 1 substitutes easily with inputs 2 and 3 but inputs 2 and 3 have a mean elasticity of substitution of .377, indicating substitution is inelastic. In the third technology substitution is very easy between input 1 and inputs 1 and 2 but inputs 2 and 3 are complements with a mean elasticity of -.254.

In brief, the following experimental design was used. For each objective function and each technology, optimal levels of the inputs were computed. For each of these optimal solutions the corresponding AES were computed as well as the elasticities of the derived demands for

inputs (IE) and the supply elasticities (SE). Thus a total of seven elasticities were computed for each technology and objective function combination. While the AES's were based solely on the optimal input levels and the technology, the choice elasticities, i.e the IE's and SE's, were computed given the objective function of the decision maker. That is, the choice elasticities corresponded to the change in demand (supply) for an input (output) given the decision makers objectives. One could make the argument that the elasticities of substitution for utility maximizers should be the change in the input ratio for the change in the price ratio of the two inputs, other prices held constant. This is not done since typically the elasticity of substitution is used to say something about the underlying technology. The alternative definition, though, could be used.

Having obtained the optimal levels of the inputs, output levels were generated by drawing observations on the error term of production from a random number generator. A multiplicative, log normally distributed error term was used to generate the stochastic error for the production function. That is, y in (2) is multiplied by the log normal random variable. The log normal had a variance of roughly .01 implying that approximately that 95 percent of the observed outputs would be no more than 20 percent above or below mean output. These output levels with their input levels and prices were then used to compute profit levels. With this information it was then possible to estimate the translog profit functions. Following Dixon et al., 100 samples, each with 50 observations, were drawn for a given technology and objective function. A corresponding 100 translog profit functions were estimated.

Substitution and price elasticities were estimated for every observation from a given set of estimates. Clearly this presents an enormous number of estimates. To achieve extensive reduction in the number of estimates, the method of averaging in Dixon et al. and Driscoll and Boisvert was used. In this method, the estimated elasticity is first averaged by observation. That is, for the first observation in each of the 100 samples, we get 100 estimates of a given elasticity. These 100 estimates are averaged to get a set of mean elasticities for each observation. These 50 means are then averaged again so that the mean estimate presented in table 1 is averaged over 5000 observations. This mean based on the 5000 estimates can then be compared with the mean of the 50 elasticities for a given parameter computed directly from the primal problem. To get some feeling for the degree of dispersion, a mean absolute deviation (MAD) statistic is also computed for every mean of the 5000 observations. The average elasticity from the 100 samples for a given observation is subtracted from the true elasticity. This difference is computed for each of the 50 observations on the true elasticities. The absolute values of the deviations are computed and then averaged over the 50 observations to get the reported MAD's.

It is helpful to first compare the true elasticities as technologies differ and the objective functions vary. When substitution is easy (technology 1), there is very little variation in the AES's and the IE's for changes in the objectives of the producer. SE does go from .57 for profit maximization to a high of 1.091 for the second utility function (negative exponential). A somewhat similar pattern emerges for technology 2 except there is a bit more variation in

the IE and the variation in the SE becomes even more pronounced for the negative exponential. In technology 2, inputs 2 and 3 do not substitute easily. In the third technology, where inputs 2 and 3 are complements, there is a bit more difference among the AES's and IE's over objective functions and less variation in the SE than for technology 2. A general conclusion based on these results is that risk aversion does not greatly affect substitution and input elasticities but does affect supply response, especially when all of the inputs do not substitute easily with each other.

The results of the estimated elasticities derived from dual translog profit function are displayed in Table 1. What first emerges from the table is that the profit function estimates the elasticities fairly accurately for technologies 1 and 2 where all inputs are substitutes. In the case where inputs 2 and 3 are complements the AES are not estimated very accurately for any objective function. For all nine AES estimates in technology 3, the signs of the means of the estimates are reversed from their true values. Moreover, the estimates of the positive AES are very inaccurate as indicated by the large MAD's associated with these parameters. This is true regardless of the objective function for technology 3.

In addition to large MAD's for the AES's for technology 3, the MAD's for the SE's are greater than 1 for the negative exponential for technologies 1 and 2. Given that the true SE's range from 2.662 for profit maximization to 6.888 for the negative exponential, this indicates a substantial loss in precision. It is important to note that the two MAD's greater than 1 occur when the objective function is maximizing utility, the cases where we would expect the approximation to be weak. What happens in technology 2 is that the estimates of SE's from the profit functions remain essentially the same for each objective function, reflecting an inability of the dual profit function to pick up changes in producer supply response. An examination of the last column of table 1 indicates that the estimates of the SE's from the profit functions do not vary much as a function of objective function. While this somewhat characterizes the estimates of the AES's and IE's, it is not true to as large a degree. For example, in technology 3 the estimates of the AES's do vary from by objective function as do the IE's for input 1 in technologies 2 and 3.

The results in Table 1, while certainly not for a large range of technologies or objective functions, suggest the following general observations: the substitutability of inputs does not vary much as a function of the objective function as reflected by the similarity of the true AES's for a given technology. The IE vary somewhat by objective function, more so when some inputs do not substitute easily or are complements. The SE's show generally more variation as a function of producer objectives. Estimating the AES, IE and SE by using a dual profit function can give fairly reliable results in some cases. Even if the underlying producer behavior is inconsistent with profit maximization, frequently the estimated elasticities can be close to the actual elasticities. Inaccuracies are most likely to occur in estimating the SE or with technologies that have some inputs as complements.

What are the implications of this analysis for efficiency studies? First, using a profit function to model expected utility maximizing behavior is not necessarily going to lead to

inaccurate predictions about producer behavior. Depending on the utility function and the underlying technology, the estimated profit functions describe producer response fairly well. However, some technologies cannot be tracked well regardless of the correctness of underlying distributions.

It should be observed that the above experiments assumed symmetric error terms and no allocative inefficiency. How would the results change if profit and utility were maximized assuming a composed error term and some allocative inefficiency? Driscoll and Boisvert show that when there is error in the choice equations of the primal problem that the resulting estimates of the cost function can be substantially inaccurate. The form of the error in the choice equations is not exactly identical to what would be true for choice equations but they would suggest that the corresponding measures of allocative inefficiency and, probably technical efficiency would be less accurate than desired. However, this would be an interesting Monte Carlo investigation to measure the extent and conditions that would lead to good and bad inferences.

Conclusions

Unlike the emphasis in Bauer's review of econometric developments and the problems still facing frontier estimation techniques, the present review has focussed on broader modelling issues. In particular, the impact of variation of producer objectives on estimation and analysis of allocative efficiency have been emphasized. The issues involving the specification of the error structure and their resultant estimators has not been emphasized. The lack of emphasis on this complex problem is due to an observation made in Bauer in reaction to a comment by Schmidt. Bauer observed that as the sample size increases, a divergence between the maximum likelihood estimator and the least squares estimator would lead a Hausman test to reject the frontier model. Thus for well-specified models of a frontier type, least squares would lead to acceptable slope parameter estimates for large samples.

Although extensive econometric testing of underlying assumptions via Hendry and Richard is to be encouraged, such testing methods are still ad hoc. Thus one is inclined to also lean to Leamer's approach of avoiding fragile inferences by estimating several variants of a model and determining if the resulting inferences are the same. This is a strength of comparing econometric and DEA approaches. Thus my recommendation to empirical research on banking studies to allocate effort to (1) obtaining quality data, (2) modelling the bank carefully with respect to production or intermediation approaches and, perhaps, dynamics, and (3) proper grouping of banks into homogeneous samples, (4) test inferences for fragility with respect to model specification changes or method of measuring efficiency.

For those who wish to investigate econometric efficiency methods, the following areas would seem fruitful: (1) for known primal technologies and producer objectives, determine variations in efficiency rankings of firms as a function of the algebraic form of the approximating dual or primal functions. (2) Develop methods for determining statistically significant differences in efficiency among firms. (3) Develop methods for identifying if producers

perceive production uncertainty as a one sided error and optimize accordingly. (4) Develop a well-behaved primal model to generate multiple outputs and test how well approximate dual forms replicate the technology and efficiency.

Table 1. Estimates of Elasticities From Profit Function

	AES12	AES13	AES23	PE1	PE2	PE3	SE
				Technology 1 - Profit Max			
TRUE	1.178	1.374	1.571	-1.011	-1.435	-1.644	.570
EST	.050	.129	.138	-1.253	-1.450	-1.721	.555
MAD	1.128	1.245	1.432	.461	.351	.254	.083
				Technology 1 - UTIL(1) Max			
TRUE	1.178	1.375	1.571	-1.139	-1.312	-1.543	.551
EST	.104	.143	.144	-1.264	-1.444	-1.718	.551
MAD	1.074	1.231	1.427	.130	.145	.178	.026
				Technology 1 - UTIL(2) Max			
TRUE	1.179	1.375	1.572	-1.239	-1.425	-1.671	1.091
EST	.126	.174	.151	-1.267	-1.449	-1.713	.542
MAD	1.052	1.200	1.420	.078	.065	.058	1.081
				Technology 2 - Profit Max			
TRUE	1.456	1.639	.364	-6.935	-1.423	-1.249	2.662
EST	.688	.902	.213	-7.36	-1.145	-1.299	2.555
MAD	.768	.736	.151	1.130	.722	.312	.379
				Technology 2 - UTIL(1) Max			
TRUE	1.472	1.656	.368	-6.251	-1.019	-1.178	2.484
EST	.763	.913	.267	-7.171	-1.135	-1.297	2.402
MAD	.709	.743	.101	1.380	.124	.130	.273

Table 1 (Continued)

				Technology 2 - UTIL(2) Max			
TRUE	1.507	1.696	.377	-6.395	-1.093	-1.218	6.888
EST	.604	.782	.232	-6.547	-1.128	-1.292	2.012
MAD	.904	.913	.144	.675	.090	.767	4.875
				Technology 3 - Profit Max			
TRUE	3.137	2.689	-.224	-8.188	-1.614	-1.489	.406
EST	-21.680	-19.036	.827	-6.705	-1.681	-1.459	.403
MAD	24.817	21.725	1.051	2.609	1.332	1.189	.139
				Technology 3 - UTIL(1) Max			
TRUE	3.217	2.758	-.230	-6.717	-1.593	-1.349	.429
EST	-24.475	-20.801	1.060	-7.454	-1.172	-1.468	.426
MAD	27.692	23.559	1.290	1.748	.203	.169	.034
				Technology 3 - UTIL(2) Max			
TRUE	3.557	3.048	-.254	-8.915	-.712	-1.281	1.239
EST	-28.964	-25.269	1.887	-8.884	-1.678	-1.468	.436
MAD	32.521	28.317	2.141	4.199	1.234	1.058	.803

Endnotes

1. The underlying technology generating the observed outputs is not a constant coefficient model. There are four different technologies, the parameters vary with the level of the inputs. The estimated production function is a constant coefficient translog model. Thus one of the underlying, standard regression assumptions is violated.

2. One bootstrapping possibility would be to estimate the slope coefficients by repeated re-sampling and then estimate (predict) the actual residuals to get confidence intervals for these predictions.

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