Bayesian efficiency analysis with a flexible form

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Publication date:
1994

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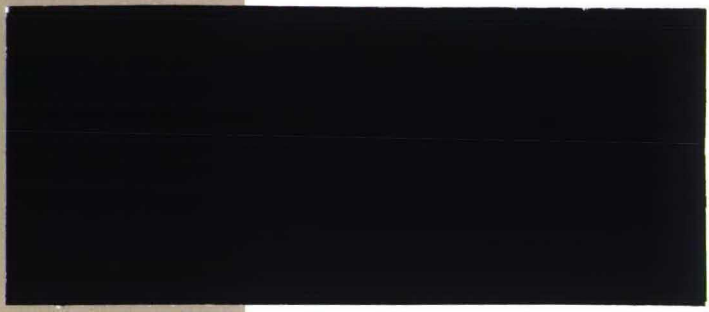
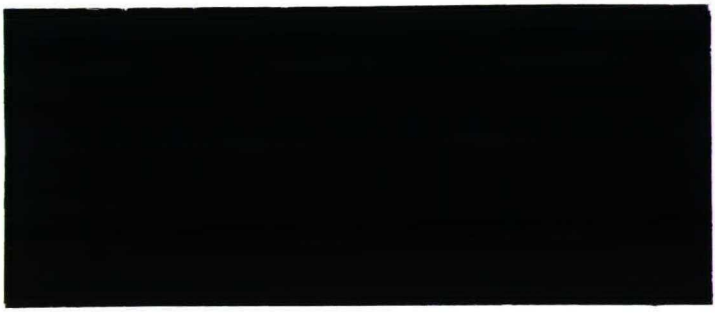
Discussion paper





Center
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Economic Research

No. 9413

BAYESIAN EFFICIENCY ANALYSIS WITH A FLEXIBLE FORM: THE AIM COST FUNCTION

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January 1994

ISSN 0924-7815

Bayesian Efficiency Analysis with a Flexible Form: The AIM Cost Function

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ABSTRACT: In this paper we describe the use of Gibbs sampling methods for drawing posterior inferences in a cost frontier model with an asymptotically ideal price aggregator, non-constant returns to scale and composed error. An empirical example illustrates the sensitivity of efficiency measures to assumptions made about the functional form of the frontier. We also examine the consequences of imposing regularity through parametric restrictions alone.

KEY WORDS: stochastic frontier; composed error model; seminonparametric; Gibbs sampling; Metropolis chain; neoclassical regularity

1. INTRODUCTION

Cost or production functions with composed error are commonly used by microeconomists in the measurement of firm inefficiency. At the same time, the development of seminonparametric methods has allowed researchers to work with very flexible cost functions without composed error. In this paper, we unite these two strands of the literature and develop Bayesian techniques for analyzing flexible functional form cost functions with composed error. We argue that such techniques allow for better understanding of firm efficiency than do traditional methods.

The paper is organized as follows. Section 2 discusses composed error models. Section 3 describes the asymptotically ideal model (AIM) which forms the basis of the seminonparametric approach we use in the paper. Section 4 introduces the AIM cost function with composed error and develops the Gibbs sampler. Section 5 applies our method to an empirical example, and Section 6 concludes.

2. COMPOSED ERROR MODELS

Composed error models were first introduced by Meeusen and van den Broeck (1977) and Aigner, Lovell and Schmidt (1977). Bauer (1990) provides a survey of the literature. The basic model is given by:

$$\ln(C_i) = h(S_i, \gamma) + z_i + v_i, \quad i = 1, \ldots, N. \tag{1}$$

This model decomposes the log of observed costs for firm i (C_i) into three parts: i) The log of the actual frontier which depends on S_i, a vector of exogenous variables, and which represents the minimum possible cost of producing a given level of output with certain input prices. Since the example used in this paper involves electrical utility companies, we believe the assumption of the exogeneity of S_i is reasonable and will not be discussed further. ii) A non-negative disturbance, z_i, which captures the level of firm inefficiency. iii) A symmetric disturbance, v_i, which captures other effects due, for instance, to measurement error.

In an empirical exercise assumptions are commonly made about these three components. Usually one takes the v_is to be i.i.d. $N(0,\sigma^2)$ and independent of the z_is, an assumption we maintain throughout this paper. Assumptions, which are not so innocuous, must also be made

about $h(.,.)$ and z_i. Typically, z_i is taken to be i.i.d. D(.), where D(.) is some one-sided distribution on $\Re^+$. Common choices for D(.) are truncated Normal, exponential or Gamma. Since interest usually centers on firm inefficiency, accurate estimation of the z_is is essential, and choosing an inappropriate D(.) may have harmful consequences. In a previous paper (van den Broeck, Koop, Osiewalski and Steel (1994), hereafter BKOS), four different choices for D(.) were used: truncated Normal, and Gamma with shape parameters 1, 2 and 3 (The Gamma with shape parameter 1 is the exponential distribution). We were able to take weighted averages across our four choices for D(.) by using posterior model probabilities as weights, and argued that such an approach was preferable to choosing one particular distribution for D(.).

Although BKOS addressed the issue of uncertainty about D(.), it assumed that $h(.,.)$ was linear in γ, an assumption we propose to relax in this paper. The exact functional form used is described in Section 3. For present purposes it is sufficient to note that estimates of z_i can be sensitive to choice of $h(.,.)$, and that most of the existing literature assumes that $h(.,.)$ takes a simple form (eg. Greene (1990) and BKOS use a variant of the Cobb-Douglas cost function). Accordingly, we intend to examine to what extent inferences on firm efficiencies, usually the prime objective of composed error models, can depend on the functional form of the frontier. By using seminonparametric methods, we intend to let the data reveal what $h(.,.)$ should be.

The use of panel data can eliminate the need for distributional assumptions to be made for z_i. However, even with panel data it is important to specify $h(.,.)$ correctly. Thus, the techniques of this paper are relevant even without the composed error framework. Indeed, it is worth stressing that the Gibbs sampling techniques developed here are innovative even for the analysis of standard cost functions. By eliminating the z_i term, our techniques provide an exact Bayesian analysis of the standard Asymptotically Ideal Model with nonconstant returns to scale. In addition, they can be extended quite easily to other nonlinear models such as the generalized translog.

3. THE ASYMPTOTICALLY IDEAL MODEL

The large amount of research that has gone into finding flexible functional forms testifies to the great importance of avoiding gross specification error. This is especially so in the case of composed error models since measures of inefficiency can be very misleading if an

inappropriate choice for h(.,.) is made. The separation of the two error terms is the main challenge in these models, and generally proves to be least robust to arbitrary assumptions made by the user. In view of this problem, we propose using seminonparametric techniques to approximate the underlying cost function.

Such techniques involve taking an expansion of a parametric form for the cost function. If properly chosen, the resulting seminonparametric cost function can, as the order of expansion increases, approach any possible function. The seminonparametric approximation we use in this paper is based on the Müntz-Szatz expansion and results in the Asymptotically Ideal Model (AIM) discussed in Barnett, Geweke and Wolfe (1991b). To motivate the advantages of the AIM, let us consider two criteria for judging a cost function: regularity and flexibility. If a cost function is regular, it satisfies the restrictions implied by economic theory; if it is flexible, it includes a wide variety of functional forms. A cost function such as the translog, which involves taking a second order Taylor Series expansion about a point, is locally flexible but not, in general, regular (although, if the underlying technology is Cobb-Douglas, then the translog is globally regular, see, eg., Caves and Christensen (1980)). The translog may be made regular at a particular data point by imposing restrictions. However, since such restrictions involve both parameters and the data, they can only be imposed at a point. In contrast, the AIM model uses the Müntz-Szatz expansion, which is globally flexible. Global regularity can be imposed on the AIM model through parametric restrictions alone, albeit at the cost of losing global flexibility.

Seminonparametric methods are useful in that they allow for the data to determine what the key properties of the cost function should be. A danger associated with some seminonparametric methods is the possibility of overfitting. Early seminonparametric models (Gallant (1981)) used Fourier expansions such that economic functions of interest were approximated using sines and cosines. Since cost functions are concave, many terms in the Fourier expansion are typically necessary, increasing greatly the risk of overfitting. It is for this reason that we favor the Müntz-Szatz expansion over the Fourier expansion; it allows for the approximation of globally regular cost functions with an expansion globally regular at every degree. The AIM model fits only that part of the data that is globally regular, thereby eliminating the risk of overfitting. For a more detailed discussion of overfitting see Barnett, Geweke and Wolfe (1991a) pp. 433-434 or Barnett, Geweke and Wolfe (1991b) p. 12.

More specifically, consider the model with one output (Q) and three input prices ($p=(p_1,p_2,p_3)'$). If constant returns to scale hold, then there exists a price aggregator, f(p), such that the frontier cost function takes the form:

$$C(Q,p) = Qf(p). \qquad (2)$$

A seminonparametric approach to this simple case would involve choosing an expansion to model f(p). Barnett, Geweke, and Wolfe (1991b) use the Müntz-Szatz expansion and call the resulting model the AIM model. Note that, while the model given above is globally flexible, in the absence of restrictions it is not globally regular, since f(p) can be any function, including non-concave or non-homogeneous (or even negative outside the range of the data). Barnett, Geweke and Wolfe describe how linear homogeneity can be imposed on f(p) in a simple way. In addition, the authors ensure that C(Q,p) is concave and increasing in input prices by requiring that all the coefficients of f(p) be positive. Their resulting AIM model is globally regular in that any order expansion will satisfy the restrictions implied by economic theory.

It is worth noting that the restriction that the coefficients of f(p) be positive is a sufficient but not necessary condition for monotonocity and concavity. Hence the AIM model with this restriction is not globally flexible; that is, there exist some regular functions which cannot be approximated by C(Q,p) once the coefficients are constrained to be positive. For instance, the inequality constraints force all inputs to be substitutes. Since it is very simple to impose, we use this positivity restriction. However, we also investigate another way of imposing regularity.

This second way involves imposing regularity only at all data points in the sample, instead of globally. The classic article which discusses the imposition of regularity conditions on flexible functional forms is Gallant and Golub (1984). These authors develop computational methods for imposing curvature restrictions at any arbitrary set of points. Their methods can be used to ensure that a cost function is concave at each data point. Imposing regularity over a grid of prices was investigated in Terrell (1993a), who describes a Bayesian method using Monte Carlo integration. The technique we use in this paper ensures that the cost function is increasing in output and nondecreasing and concave in input prices at each point in the sample. In practice, at each draw from the Gibbs sampler we check whether all of the regularity conditions hold at each data point. If any of the regularity conditions are violated at any data point, then the Gibbs

draw is discarded. This method ensures that we do not reject any cost function that is regular at all the data points, and thus retains the global flexibility of the Müntz-Szatz expansion in the space of all locally regular cost functions.

Non-constant returns to scale that vary with output can be incorporated by specifying the frontier cost function as:

$$C(Q,p) = Q^{\beta_1+\beta_2 \ln Q} f(p) . \qquad (3)$$

The above cost frontier will be adopted here with an AIM(q) form for f(p), where q is the order of the expansion. The Müntz-Szatz expansion has yet to be explicitly defined, as its general formulation is complicated. Once we impose linear homogeneity, however, it can be greatly simplified. Below we give the linearly homogenous Müntz-Szatz expansion for f(p) for q=1 and 2, in the case with three inputs. (The evidence we obtain in our empirical example clearly suggests that q=2 is sufficient for our application).

f(p) for use in AIM(1)

$$f(p) = \alpha_1 p_1 + \alpha_2 p_2 + \alpha_3 p_3 + \alpha_4 p_1^{\frac{1}{2}} p_2^{\frac{1}{2}} + \alpha_5 p_1^{\frac{1}{2}} p_3^{\frac{1}{2}} + \alpha_6 p_2^{\frac{1}{2}} p_3^{\frac{1}{2}}$$

f(p) for use in AIM(2)

$$\begin{aligned} f(p) = {} & \alpha_1 p_1 + \alpha_2 p_2 + \alpha_3 p_3 + \alpha_4 p_1^{\frac{1}{2}} p_2^{\frac{1}{2}} + \alpha_5 p_1^{\frac{1}{2}} p_3^{\frac{1}{2}} + \alpha_6 p_2^{\frac{1}{2}} p_3^{\frac{1}{2}} \\ & + \alpha_7 p_1^{\frac{3}{4}} p_2^{\frac{1}{4}} + \alpha_8 p_1^{\frac{3}{4}} p_3^{\frac{1}{4}} + \alpha_9 p_2^{\frac{3}{4}} p_3^{\frac{1}{4}} + \alpha_{10} p_1^{\frac{1}{4}} p_2^{\frac{3}{4}} + \alpha_{11} p_1^{\frac{1}{4}} p_3^{\frac{3}{4}} \\ & + \alpha_{12} p_2^{\frac{1}{4}} p_3^{\frac{3}{4}} + \alpha_{13} p_1^{\frac{1}{2}} p_2^{\frac{1}{4}} p_3^{\frac{1}{4}} + \alpha_{14} p_1^{\frac{1}{4}} p_2^{\frac{1}{2}} p_3^{\frac{1}{4}} + \alpha_{15} p_1^{\frac{1}{4}} p_2^{\frac{1}{4}} p_3^{\frac{1}{2}} \end{aligned}$$

Linear homogeneity in input prices is assured, since the exponents in each term sum to one. If each element of $\alpha=(\alpha_1,..,\alpha_k)'$, (k=6 for AIM(1) and k=15 for AIM(2)) is positive, then f(p) is positive, increasing and concave for all positive input prices. Global regularity is thus ensured by imposing $\alpha \in R_+^k$, whereas for local regularity we check the neoclassical conditions for each data point whenever α lies outside the positive orthant yet leads to f(p)>0 for all observed prices. It is worth noting that the first degree expansion yields a cost function identical to the commonly used generalized Leontief model.

4. THE GIBBS SAMPLER

The Gibbs sampler is a technique for obtaining a random sample from a joint distribution by taking random draws only from the full conditional distributions. A detailed description of the technique can be found in Casella and George (1992) and Gelfand and Smith (1990).

If we use (3) to model the log of the cost frontier, $h(S_i,\gamma)$ in (1), we obtain the model used in this paper:

$$\ln(C_i) = \beta_1 \ln(Q_i) + \beta_2 \ln^2(Q_i) + \ln(f(p_i)) + z_i + v_i, \qquad (4)$$

where v_i is i.i.d. $N(0,\sigma^2)$, z_i is chosen to be i.i.d. exponential with parameter λ and $p_i=(p_{1i},p_{2i},p_{3i})'$. It would be trivial to allow z_i to take other forms. However, we do not do so here in order to focus analysis on the modelling of the frontier. The exponential stochastic specification was found in BKOS to be most robust to changes in prior assumptions about λ. In all cases, we assume a prior density which is flat on $\ln(\sigma^2)$ and $\beta=(\beta_1,\beta_2)'$.For the first set of results the elements of α are restricted to be positive. This imposes the global regularity restrictions described in Section 3. In addition, we impose restrictions on β to ensure that the cost function is increasing in output, but, in the present example, this is a non-binding constraint. The second set of results is based upon a prior which ensures that the regularity conditions are satisfied at each data point. In order to ensure that the posterior is proper, we put an informative prior on λ^{-1} (see Ritter and Simar (1993)). That is,

$$p(\alpha,\sigma^2,\beta,\lambda^{-1}) \propto \sigma^{-2} p(\lambda^{-1})\, p(\alpha),$$

where $p(\alpha)$ takes two different forms: i) $p(\alpha)=1$ if all the elements of α are positive and $=0$ otherwise (we shall call this the global regularity prior); and ii) $p(\alpha)=1$ if all of the regularity conditions are satisfied for every observation and $=0$ otherwise (the local regularity prior). We take a Gamma prior for λ^{-1} where the hyperparameters are elicited as described in BKOS. It suffices to note here that we select the prior median (r^*) for the efficiency, $r_i=\exp(-z_i)$, to be .875, which leads to $p(\lambda^{-1})=f_G(\lambda^{-1}\,|\,1,-\ln(r^*))$, where $f_G(.\,|\,b,c)$ denotes the Gamma density with mean b/c and variance b/c^2. These assumptions define our Bayesian model from which posterior inferences on the parameters or the r_is can be made.

In BKOS we carried out a Bayesian analysis of a similar model using Monte Carlo

integration with importance sampling. In a subsequent paper (Koop, Steel and Osiewalski (1993), hereafter KSO), we argued that the computational difficulties surrounding Monte Carlo integration with importance sampling were truly daunting and recommended the use of Gibbs sampling methods instead. The Gibbs sampler derived in KSO was found to work very well and yielded very accurate results with a relatively light computational burden. However, the Gibbs sampler in KSO was derived for a Cobb-Douglas price aggregator in (3), implying that h(.,.) was linear in γ. Because the log of the AIM cost function used in this paper is not linear in α, the Gibbs sampler is different from that developed in KSO. It is worth emphasizing that, although the Gibbs sampler derived here is for the extension to the AIM cost function given in (3), similar methods can be used to carry out a Bayesian analysis of other nonlinear cost functions.

To develop our Gibbs sampler we begin with some notation: let $y_i=-\ln(C_i)$, $x_i=(-\ln(Q_i)$ - $\ln^2(Q_i))'$, and $w_i'\alpha=f(p_i)$ (i.e. let w_i contain the decreasing fractional powers of p_i given in Section 3). Furthermore, let X, z, y and w_α indicate the vectors or matrices containing data on all firms for x_i, z_i, y_i and $\ln(w_i'\alpha)$. Since, conditionally on α, the frontier is linear, we can draw on results from KSO to state:

$$p(\beta,\sigma^{-2} \mid Data,z,\alpha,\lambda^{-1}) = p(\beta,\sigma^{-2} \mid Data,z,\alpha) = f_G(\sigma^{-2} \mid \frac{N-2}{2}, \frac{1}{2}(y+z+w_\alpha-X\beta)'(y+z+w_\alpha-X\beta))\, f_N(\beta \mid \hat{\beta}, \sigma^2(X'X)^{-1}), \quad (5)$$

where

$$\hat{\beta}=(X'X)^{-1}X'(y+z+w_\alpha),$$

and $f_N(.|a,A)$ denotes the Normal density with mean vector a and covariance matrix A. Furthermore, given z, λ is independent of all the data and the other parameters such that:

$$p(\lambda^{-1} \mid Data,z,\alpha,\beta,\sigma^{-2}) = p(\lambda^{-1} \mid z) = f_G(\lambda^{-1} \mid N+1, z'\iota - \ln(r^*)), \quad (6)$$

where ι is an Nx1 vector of ones. The conditional posterior for z takes the form of a product of independent truncated Normal densities:

$$p(z \mid Data, \alpha, \beta, \lambda^{-1}, \sigma^{-2}) \propto f_N(z \mid X\beta - w_\alpha - y - \frac{\sigma^2}{\lambda}\iota, \sigma^2 I_N) \prod_{i=1}^{N} I(z_i \geq 0) \quad (7)$$

where I(.) is the indicator function and I_N is the NxN identity matrix.

Given β, σ^{-2} and z we have a nonlinear regression model in α, which leads to:

$$\begin{aligned} p(\alpha \mid Data, z, \beta, \lambda^{-1}, \sigma^{-2}) &= p(\alpha \mid Data, z, \beta, \sigma^{-2}) \\ &\propto p(\alpha) \exp\left[-\frac{1}{2\sigma^2} \sum_{i=1}^{N} (y_i - x_i'\beta + z_i + \ln(w_i'\alpha))^2\right]. \end{aligned} \quad (8)$$

A Gibbs sampler can be set up in terms of conditional densities (5), (6), (7) and (8). Note that, with the exception of (8), it is easy to take random draws from all of these densities. To take draws from (7) we use the truncated Normal random number generator suggested in Geweke (1991), while (5) and (6) involve Normal and Gamma distributions only.

It remains to discuss random number generation from (8), which does not take the form of any standard density. To this end, we set up an independence Metropolis algorithm (see Tierney (1991) for a theoretical discussion and Chib and Greenberg (1992) and Marriott, Ravishanker, Gelfand and Pai (1993) for applications). Like the Gibbs sampler, the Metropolis algorithm, originally proposed by Metropolis *et al.* (1953), is based on a Markov chain. We use a special case of the Metropolis implementation in Hastings (1970). A Markovian transition kernel drives the chain by generating candidate values for the next draw. These candidates are then either accepted with a certain probability, or rejected, in which case the chain remains at the current value. The independence Metropolis chain draws candidates independently and always from the same density, $\theta(.)$. So, on the ith pass, this algorithm generates a candidate, α^*, from $\theta(\alpha)$. The random draw from (8), α^i, is then either α^* or α^{i-1} with a certain probability. If the procedure stays at the same value for α over several passes, this value acquires more and more weight. As a consequence, the algorithm will generate a serially correlated sample from (8). Tierney stresses that this method works best if $\theta(\alpha)$ is a good approximation to the actual posterior.

Since equation (8) takes the form of a nonlinear regression model in α, we let $\theta(\alpha)$ be a multivariate Student-t distribution multiplied by the appropriate prior (i.e. for the global regularity prior the Student-t is truncated to the non-negative orthant and for the local regularity prior it is truncated to the region where regularity is imposed at all sample points). We use the

algorithm described in Geweke (1991) to draw from the truncated Student distribution. The mean, α_0, and covariance matrix, Ω, are calibrated on the basis of an iterative procedure starting with approximate generalized least squares results. The approximate GLS procedure is based on the fact that $y^*=\exp(X\beta-y-z)$ is approximately linear in α. In particular,

$$y^* = w'\alpha \exp(v) \cong w'\alpha(1+v) = w'\alpha + v^*,$$

where v^* is Normal with standard deviation $w'\alpha\sigma$. Hence, given starting values for β and z, we can use two- or three-step GLS to obtain an estimate for α as well as a covariance matrix. When we impose global regularity, negative values in α_0 are restricted to zero due to the truncation of α.

Thus, we take candidate draws from

$$\theta(\alpha) \propto p(\alpha) f_S^k(\alpha \mid \nu, \alpha_0, A),$$

where $p(\alpha)$ is our prior for α which ensures nonnegativity or regularity in all data points and $f_S^k(.\mid \upsilon,\alpha_0,A)$ is the k-variate Student-t density with υ degrees of freedom, location vector α_0 and precision matrix A (ie. covariance matrix $\Omega=(\upsilon/\upsilon\text{-}2)A^{-1}$). Moreover, we denote by $\tau(\alpha)$ the ratio of the kernels of $p(\alpha \mid \text{Data},z,\beta,\sigma^2)$ and $\theta(\alpha)$:

$$\tau(\alpha) = \frac{\exp\left[-\frac{1}{2\sigma^2}\sum_{i=1}^{N}(y_i - x_i'\beta + z_i + \ln(w_i'\alpha))^2\right]}{\left[1+\frac{1}{\nu}(\alpha-\alpha_0)'A(\alpha-\alpha_0)\right]^{-\frac{\nu-k}{2}}}.$$

The degrees of freedom parameter, υ, is chosen on the basis of computational considerations. It is important that $\theta(\alpha)$ have tails at least as fat as (8) to avoid the algorithm getting stuck at a tail value for α with very high $\tau(\alpha)$. Here, we set $\upsilon=3$. Our independence Metropolis algorithm for drawing α^i can then be defined as follows:

Step 1: Take a draw, α^*, from $\theta(\alpha)$.

Step 2: Calculate $K=\tau(\alpha^*)/\tau(\alpha^{i-1})$.

Step 3: Take a draw, u, from the uniform (0,1) distribution.

Step 4: If $K > u$ then $\alpha^i = \alpha^*$, else $\alpha^i = \alpha^{i-1}$.

In practice, this algorithm works quite well, provided α_0 and A are chosen carefully. Relative to α, the Gibbs sampler seems much less sensitive to the choice of initial values for β, σ^{-2} and λ^{-1}. Tierney (1991) mentions the combination of Gibbs and Metropolis steps in a single Markov chain strategy, as used here, and notes that such a hybrid chain is uniformly ergodic provided $\tau(\alpha)$ is bounded, which leads to the strongest form of convergence.

5. EMPIRICAL RESULTS

The application discussed in this section is the same as that analyzed in BKOS, KSO and Greene (1990), who provides a complete listing of the data. The data set contains observations from $N = 123$ electric utility companies in the United States in 1970. In addition to output and cost figures, the data set contains information on three input prices: labor price (p_1), capital price (p_2) and fuel price (p_3).

The version of the Gibbs sampler we adopt is that described in Gelfand and Smith (1990). That is, instead of starting the Gibbs sampler and then taking one long run, we take several shorter runs each starting at the same initial values. We carry out M runs, each containing L passes, and keep only the Lth pass out of these runs.

The issue of whether to use one long run from the Gibbs sampler (sequential Gibbs sampling) or to restart every Lth pass (parallel Gibbs sampling) has been discussed in the literature (see, for example, Tanner (1991), Carlin *et al.* (1992), Casella and George (1992), Gelman and Rubin (1992) and Raftery and Lewis (1992)). The question of which variant is preferable is no doubt a problem-specific one, but in our application, the restarting method was found to work best. As in KSO, restarting is required to break serial correlation and to prevent the path from becoming "temporarily trapped in a nonoptimal subspace" (Tanner (1991), p. 91; see also Zeger and Karim (1991) and Gelman and Rubin (1992)). Furthermore, some experimentation revealed that the relative numerical efficiencies from the parallel sampler were roughly ten times as big as those from the sequential sampler.

We set starting values for α in AIM(1) to α_0 determined by the procedure described in Section 4 and choose posterior means from KSO as starting values for the other parameters and

$r_i=\exp(-z_i)$, $i=1,..,N$. For AIM(2) we start α at the posterior means from the AIM(1) model for $\alpha_1,..,\alpha_6$ and at zero for the other elements of α, retaining KSO starting values for the rest of the parameters and for the r_is.

It is extremely important to evaluate the accuracy of our Gibbs sampling methods. To this end, we present numerical standard errors (NSEs) calculated using the formula given in Geweke (1992). This formula involves the use of spectral methods for which we use a Parzen window with truncation point $2M^{1/2}$. For a more thorough discussion of the practical details required to implement our Gibbs sampler, the reader is referred to KSO.

We have experimented with different starting values and values for L. In addition, we allowed for the Metropolis chain on α to generate R proposals for every drawing of $(\beta,\sigma^{-2}, \lambda^{-1},z)$. Finally, we settled on $L=50$ and $R=1$. Results with $R>1$ (up to 50) were virtually identical, provided we did parallel Gibbs sampling with large enough L.

Results with $L=50$ are given in Tables 1 to 3 and Figures 1 to 4. Tables 1 and 2 contain posterior means and standard deviations of all the parameters along with NSEs corresponding to the means. In Table 3, results from KSO (based on $M=10,000$ with $L=5$) are added for comparison. From Tables 1 and 2, we note that: i) NSEs are very small; hence our estimates are quite accurate and RNEs (not presented here) indicate that the restarting has partly broken the positive serial correlation of the draws, leading to roughly the same numerical efficiency as i.i.d. sampling from the posterior for all the parameters. ii) Both under global and local regularity, the results of AIM(1) and AIM(2) are very similar in the sense that both models lead to essentially identical frontiers and efficiency measures. This indicates that we need not proceed with higher order approximations (ie. $q>2$). Moreover, the AIM(3) specification already involves 45 parameters in the price aggregator. However, posterior moments of common parameters clearly indicate substantial differences between the AIM specifications used here and the Cobb-Douglas frontier used in KSO (KSO posterior moments are not reported here).

Returns to scale (RTS) can vary across firms. The RTS, corresponding to the posterior means of β, for the minimum, median and maximum output firms are 2.42, 1.05 and .89, respectively, for the locally regular AIM(1) and AIM(2) specifications. These results indicate that average sized firms tend to exhibit roughly constant RTS while small (large) firms tend to exhibit increasing (decreasing) RTS.

Table 3 and Figure 1 present evidence on the efficiency measures. We define $r_i=\exp(-z_i)$ as our measure of firm specific efficiency and r_f as the efficiency of a hypothetical average unobserved firm (see BKOS for details). Table 3 presents posterior moments of r_f and r_i $(i=1,..,5)$ for the AIM(1) and AIM(2) expansions. Two major findings are immediately apparent: using the AIM model, efficiency measures are much closer to full efficiency than in KSO as well as showing much less variation over firms. These results are reinforced in Figure 1 which plots r_f for all three models considered. Finally, we note that AIM(1) and AIM(2) lead to virtually identical inference on efficiencies, regardless of the way we impose regularity conditions. In particular, the posterior densities of r_f corresponding to these models are indistinguishable (see Figure 1).

It cannot be overemphasized that the results presented in this section are not caused by overfitting, since the restrictions imposed on our cost frontier ensure that it is regular. Hence our frontier only fits that part of the data that is regular. Evidence obtained for AIM models without imposing the regularity restrictions on α indicates that these restrictions are indeed binding. However, there is an important difference between imposing these regularity conditions locally and globally. Positivity restrictions on α lead to substantially lower values of $p(y|X,z,\alpha,\beta,\sigma^2,\lambda)$, and thus to an estimated integrating constant four orders of magnitude smaller than in the case of imposing regularity at all data points only. The measure of fit described in the Appendix is 0.028 for the globally regular AIM(1) and is improved to 0.026 when regularity is imposed locally. However, both AIM(1) models fit better than the Cobb-Douglas frontier in KSO, which leads to a fit measure of 0.030. The most striking difference between the two ways of imposing regularity involves the posterior mean of α, as shown in Table 1. Even though there is virtually no posterior evidence of complementarity of inputs in the locally regular model, restricting α to the positive orthant is by no means innocuous. In the AIM(1) specification complementarity of inputs pairs corresponds to negative values for α_4 to α_6. Figures 2-4 plot the posterior density function of these coefficients, and clearly illustrate both the lack of complementarity and the influence of restricting the entire α-vector to lie in the positive orthant (see, in particular, Figure 2).

Analogously, imposing the regularity conditions locally improves the fit for AIM(2) from 0.029 to 0.026, and induces substantial changes in the posterior characteristics of α. In both the

locally regular AIM(1) and AIM(2), most of the rejected α-vectors violated the monotonicity condition (48% of all drawings for AIM(1) and 59% for AIM(2)). The concavity restriction was only violated in 1% and 2% of all drawings for AIM(1) and AIM(2), respectively. In view of the negative means of α_1 and especially α_2, this result is not surprising.

On the basis of simulated data, Terrell (1993b) also concludes that global regularity comes at a great cost of flexibility, even when all inputs are substitutes.

In our parallel Gibbs setup with L=50, the computational requirements of checking the regularity restrictions at each data point are, in fact, quite moderate. As these conditions are only checked at the end of every parallel Gibbs chain of length 30, CPU time required is less than 20% higher than in the case of global regularity. All computations were performed using Gauss on a 486-50 PC and typically ran overnight.

Finally, if we consider the proportion of the lack of fit that derives from the symmetric error component, v_i, we observe substantial differences between the AIM frontiers used here and the Cobb-Douglas specification for KSO. These proportions are 82% (78%) for AIM(1) (AIM(2)) under global regularity and 76% (78%) under local regularity, but only 45% for the KSO specification. Thus, apart from fitting the data worse, the Cobb-Douglas specification allocates more of the residual to inefficiency than do the AIM specifications.

Insofar as they hold in other data sets, the findings of this section convey a serious warning to empirical researchers working with stochastic frontier models. Estimated efficiency measures are found to be quite sensitive to the choice of functional form for the frontier.

6. CONCLUSIONS

This paper carries out a Bayesian analysis of the AIM cost function with composed error. Three important contributions to the existing literature are made: 1) On a theoretical level, the paper develops a Gibbs sampler for analyzing the AIM cost function with non-constant returns to scale and with composed error. It emphasizes that the techniques developed can be easily extended to other nonlinear models as well as to models without composed error. 2) Empirical results presented here indicate that measured efficiencies can be very sensitive to the choice of functional form for the frontier. In fact, the cost function based on the AIM aggregator corresponds to a very different frontier from that based on the Cobb-Douglas aggregator. This

latter finding should be a warning to researchers working with stochastic frontier models. 3) Imposing regularity conditions in AIM specifications through nonnegativity restrictions is found to reduce the span of the Müntz-Szatz expansion to a subset substantially smaller than the space of all neoclassical functions, even in the case of substitutability of inputs.

ACKNOWLEDGEMENTS: We would like to thank Christian Ritter, three anonymous referees and an associate editor for helpful suggestions, and are grateful to John Geweke for providing the computer code for sampling from the truncated multivariate Student-t distribution. The second author would like to acknowledge the hospitality of Tilburg University and support from the Polish Committee for Scientific Research (KBN Grant Number 1 P110 025 05).

Appendix: Measuring Fit in Composed Error Models

The actual deviation from the theoretical frontier is $\epsilon_i = v_i + z_i$, where v_i and z_i have the properties described in the body of the paper. Thus, a natural sampling characteristic of fit is

$$E(\epsilon_i^2 \mid \sigma^2, \lambda) = E(v_i^2 \mid \sigma^2) + E(z_i^2 \mid \lambda)$$
$$= \sigma^2 + var(z_i \mid \lambda) + E^2(z_i \mid \lambda) = \sigma^2 + 2\lambda^2 .$$

From a Bayesian standpoint, this is a random variable, so that we use as a measure of lack of fit the posterior expectation:

$$E(\sigma^2 + 2\lambda^2 \mid Data) = E(\sigma^2 \mid Data) + 2\,[\,var(\lambda \mid Data) + E^2(\lambda \mid Data)\,] .$$

All the quantities in the equation above can easily be calculated in our Gibbs sampling procedure.

The same posterior measure of fit can be obtained in a predictive Bayesian fashion. Consider an unobserved (forecasted) firm, for which the deviation is $\epsilon_f = v_f + z_f$. Assuming independent sampling, the posterior expected squared deviation for this unobserved firm is

$$E(\epsilon_f^2 \mid Data) = \int_0^\infty \int_0^\infty E(\epsilon_f^2 \mid \sigma^2, \lambda)\, p(\sigma^2, \lambda \mid Data)\, d\sigma^2 d\lambda$$
$$= E(\sigma^2 + 2\lambda^2 \mid Data) .$$

It should be stressed that this is not the same measure of fit as that used in BKOS. All the models in that paper used the same theoretical frontier and, hence, ignored the systematic part of the deviation. The measure used in BKOS is given by

$$TV_f = var(\epsilon_f \mid Data) = E(\epsilon_f^2 \mid Data) - E^2(z_f \mid Data) .$$

For stochastic frontier models, $E(\epsilon_f^2 \mid Data)$, which measures the distance from the theoretical frontier of the average firm, seems a more sensible goodness of fit measure than $var(\epsilon_f \mid Data)$.

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Table 1: Posterior Moments of AIM(1) Parameters

	Globally	Regular	AIM(1)	Locally	Regular	AIM(1)
	Mean	NSE	St. Dev.	Mean	NSE	St. Dev.
β_1	.293	3.86E-4	.016	.311	3.64E-4	.015
β_2	.038	3.80E-5	1.51E-3	.037	3.40E-5	1.43E-3
σ^{-2}	44.162	.179	6.942	51.155	.189	8.445
λ^{-1}	23.862	.222	9.123	22.098	.179	9.047
σ^2	.023	----	3.62E-3	.020	----	3.26E-3
λ	.048	----	.017	.052	----	.019
α_1	1.66E-6	2.10E-8	1.05E-6	-2.70E-6	3.61E-8	1.77E-6
α_2	1.12E-4	2.04E-6	7.53E-5	-2.64E-4	3.27E-6	1.36E-4
α_3	9.95E-4	9.08E-6	3.68E-4	1.21E-3	8.47E-6	4.05E-4
α_4	1.31E-5	2.57E-7	9.59E-6	6.60E-5	5.13E-7	2.47E-5
α_5	9.84E-5	9.10E-7	3.51E-5	1.09E-4	7.90E-7	4.05E-5
α_6	3.41E-4	4.18E-6	2.01E-4	3.76E-4	5.36E-6	2.48E-4

Note to Table 1: Results are based on L=50 and M=1600 for the globally regular and L=50 and M=2091 for the locally regular case.

Table 2: Posterior Moments of AIM(2) Parameters

	Globally	Regular	AIM(2)	Locally	Regular	AIM(2)
	Mean	NSE	St. Dev.	Mean	NSE	St. Dev.
β_1	.324	4.35E-4	.019	.312	3.95E-4	.019
β_2	.036	3.80E-5	1.68E-3	.037	3.65E-5	1.65E-3
σ^{-2}	45.029	.153	7.793	49.867	.176	8.490
λ^{-1}	21.739	.204	8.626	22.737	.280	9.507
σ^2	.023	----	4.01E-3	.021	----	3.46E-3
λ	.053	----	.019	.051	----	.019
α_1	1.05E-6	1.76E-8	7.97E-7	-2.89E-6	6.15E-8	2.19E-6
α_2	6.64E-5	1.39E-6	5.43E-5	-2.74E-4	3.60E-6	1.58E-4
α_3	9.80E-4	6.62E-6	3.04E-4	1.19E-3	1.38E-5	4.80E-4
α_4	1.04E-5	2.24E-7	8.22E-6	7.29E-5	6.84E-7	3.09E-5
α_5	5.91E-5	6.18E-7	2.72E-5	1.09E-4	1.18E-6	4.87E-5
α_6	1.68E-4	3.27E-6	1.19E-4	3.79E-4	7.00E-6	2.79E-4
α_7	2.87E-6	5.36E-8	2.26E-6	-6.08E-7	1.70E-7	6.96E-6
α_8	5.06E-6	6.61E-8	3.24E-6	-2.45E-7	1.64E-7	7.15E-6
α_9	4.13E-6	7.40E-8	3.11E-6	-1.68E-7	1.75E-7	7.35E-6
α_{10}	6.48E-6	9.44E-8	4.11E-6	-1.88E-7	1.89E-7	7.64E-6
α_{11}	3.62E-6	5.66E-8	2.79E-6	-9.50E-8	2.08E-7	7.48E-6
α_{12}	5.83E-6	8.76E-8	3.84E-6	7.08E-8	1.84E-7	7.39E-6
α_{13}	4.53E-6	7.47E-8	3.15E-6	1.16E-7	1.98E-7	7.39E-6
α_{14}	5.15E-6	8.68E-8	3.56E-6	1.87E-7	1.79E-7	7.43E-6
α_{15}	4.69E-6	9.01E-8	3.34E-6	9.57E-8	1.89E-7	7.67E-6

Note to Table 2: Results are based on L=50 and M=1600 for the globally regular and L=50 and M=1615 for the locally regular case.

Table 3: Posterior Moments of Efficiency Measures

	r_f	r_1	r_2	r_3	r_4	r_5
Globally	Regular	AIM(1)				
Mean	.955 [3.6E-4]	.958	.976	.952	.960	.969
St. Dev.	.048	.042	.023	.046	.039	.030
Locally	Regular	AIM(1)				
Mean	.951 [3.5E-4]	.943	.974	.951	.958	.970
St. Dev.	.052	.053	.025	.047	.041	.030
Globally	Regular	AIM(2)				
Mean	.950 [4.4E-4]	.947	.974	.947	.957	.966
St. Dev.	.052	.050	.024	.051	.041	.033
Locally	Regular	AIM(2)				
Mean	.952 [4.8E-4]	.945	.975	.954	.957	.970
St. Dev.	.051	.051	.025	.045	.041	.028
KSO						
Mean	.918 [8.9E-4]	.736	.972	.943	.925	.963
St. Dev.	.079	.112	.027	.049	.059	.034

Note to Table 3: KSO indicates results from the exponential model with linear frontier analyzed in KSO (M=10,000 and L=5). Values in square brackets are NSEs.

FIGURE 1: POSTERIOR EFFICIENCIES

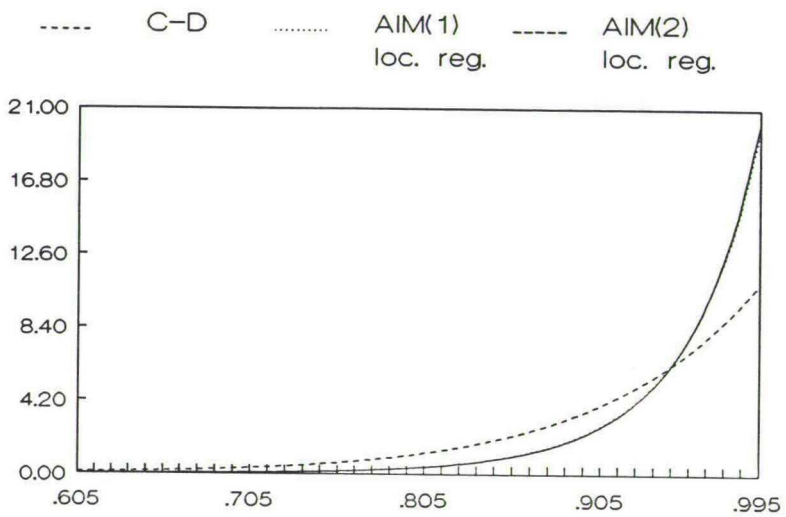


FIGURE 2: POSTERIOR OF ALPHA4 IN AIM(1)

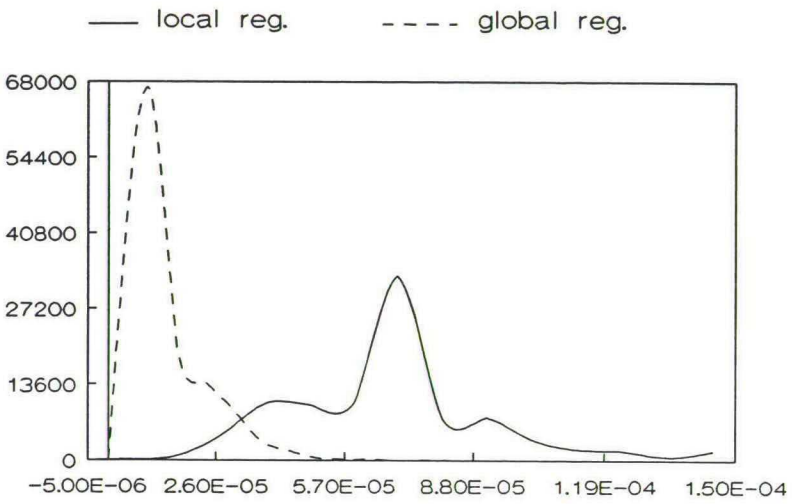


FIGURE 3: POSTERIOR OF ALPHA5 IN AIM(1)

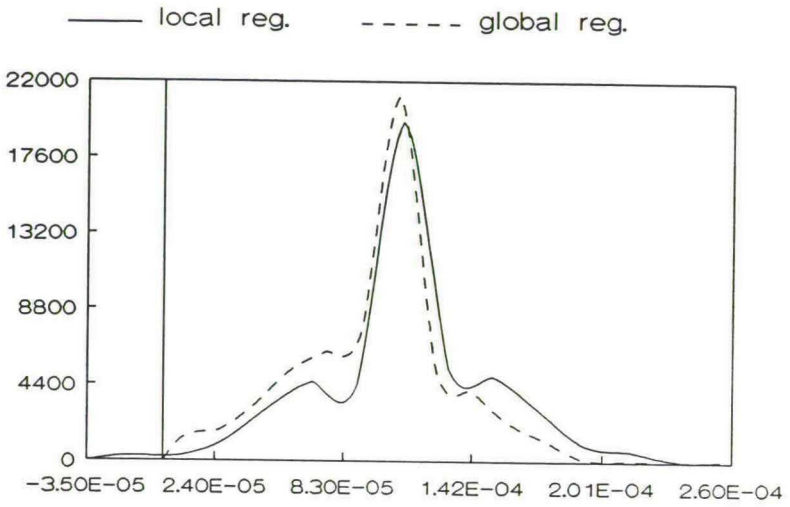
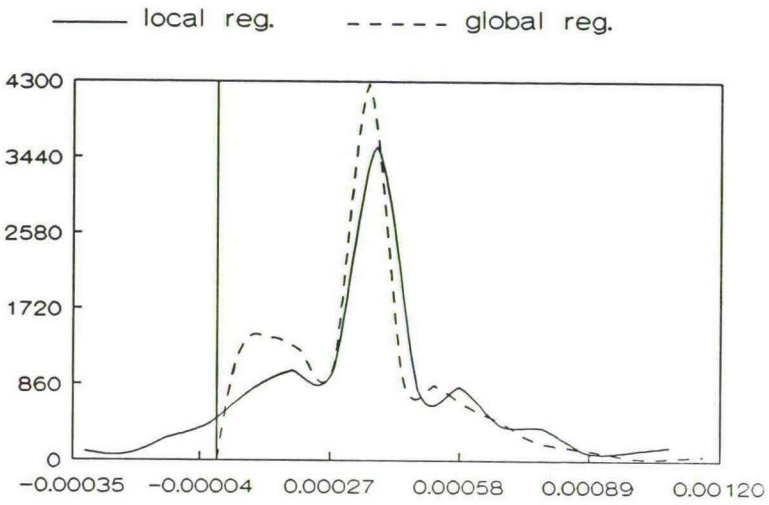


FIGURE 4: POSTERIOR OF ALPHA6 IN AIM(1)



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