Does Deregulation Change Economic Behavior of Firms?

A Latent Class Approach

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Abstract

Cost minimization and profit maximization behavioral assumptions are most widely used in microeconomic theory to analyze firm behavior. However, in practice researchers do not know whether every firm in the sample maximizes profit or minimizes cost. In this paper we address this problem via a latent class modeling approach in which we first consider the cost minimization problem (first class) and then the profit maximization problem (second class). The two problems are then mixed and the probabilities of class membership are made functions of covariates. This approach does not require researchers to know which firms maximize profit and which ones minimize cost. On the contrary, it helps us to determine not only which firms behave like profit maximizers but also why and what differentiates them from firms that failed to maximize profit. The new technique is illustrated using a panel data for the US airlines. The empirical findings suggest that very few airlines maximize profit consistently (if at all) and that deregulation had a positive impact on the chances of behaving like profit maximizers, although very few airlines continue to maximize profit even after the deregulation.

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1. Introduction

Estimation of the production technology using dual cost and profit functions (McFadden, 1978; Chambers, 1988) is not new. The dual cost and profit function formulations explicitly assume that producers either minimize cost or maximize profit. In doing so these dual models clearly state which variables (that is, whether only inputs or both inputs and outputs) are endogenous (choice) and which are exogenous to the producers. This is in contrast to the primal approach (production/distance function) in which the model doesn't take the input (output) choice decisions explicitly into account.

In practice, researchers using a dual approach have to decide whether the cost or the profit function should be used. Most often the decision is in favor of a cost function without much justification from either theoretical or empirical viewpoints.[1] The main difference between the cost and profit function is that output is treated as exogenous in the cost function while in the profit function an additional condition for optimal output choice is included. Thus, instead of using a profit function explicitly one can use a cost function along with the optimal output decision rule as an additional equation. The advantage of doing this is that one can test econometrically whether the data support cost minimization or profit maximization behavior (Schankerman and Nadiri, 1986; Kulatilaka, 1985). In spite of this, applied researchers arbitrarily decide using either a cost or a profit function to estimate the underlying production technology.

Following the methodology developed by Schankerman and Nadiri (1986) in the context of testing whether firms are in long-run equilibrium, one may formally test whether the producers in the given sample are cost minimizers or profit maximizers. Based on the test results, for example, one will be using either a cost or a profit function formulation. This implictly assumes that all producers in the sample behave in the same way. In reality, firms in a particular industry, although using the same technology, may differ in terms of their behavior. For example, some producers might minimize cost because of high adjustment cost (*i.e.*, it may not be optimal for such producers to adjust their outputs to the profit maximizing level), while for others it might be optimal to maximize profit. Again a producer might be minimizing cost for

[1] For example, in banking applications, Mester (1993) and Grifell and Lovell (1997) grouped banks into private and savings banks; Kolari and Zardkoohi (1995) estimated separate costs functions for banks grouped in terms of their output mix.

some time periods and then switch to profit maximizing behavior and vice versa, depending on adjustment cost associated with outputs. In such a case estimating a single cost (profit) function assuming that all the producers behave in the same manner will not be appropriate. That is, by imposing cost minimization behavior on producers who are profit maxizers and vice versa, the estimate of the underlying technology may be biased. Consequently, features of the technology such as returns to scale, elasticities, technical change, *etc*., estimated using the wrong technology will be wrong.

If one knows which producers are cost minimizers and which are maximizing profit, then one can split the sample into two classes. A cost function is estimated using the sample observations in the first class, and a profit function approach is used for the producers in the second class. This procedure is not *efficient* because the above approach doesn't take into account the fact that the underlying technology is exactly the same for all producers. The other practical problem is that no one knows before hand which producers are cost minimizers and which are profit maximizers. Consequently, this approach cannot be used in practice.

To exploit the information in the data more efficiently and avoid biases resulting from misspecifying behavioral objectives of firms in the absence of any *a priori* classification rule, we propose using a Latent Class Model[2] (hereafter LCM). In this model both the technology and the probability of a particular class membership (cost minimization, profit maximization, etc.) are estimated *simultaneously*. By doing so we assume that every producer has a probability of being in either group. Thus all the observations in the sample are used to estimate the underlying technology (that is the same for all) and the probability of their class membership. The advantage of the LCM is that it is not necessary to impose *a priori* criterion to identify which producers are in what class. Furthermore, the LCM approach is flexible enough to accommodate switching behavior on the part of a producer when panel data is available. Moreover, we can formally examine whether some exogenous factors are responsible for the presence or absence of profit maximizing (cost minimizing) behavior by making the probabilities functions of exogenous variables. When panel data is available, we do not need to assume that producers behave like

[2] See Greene (2002) for a survey of latent class models.

profit maximizers all the time, so we can accommodate switching behavior, and determine when they behaved like profit maximizers and when they acted as cost minimizers.

The rest of the paper is organized as follows. In Section 2 we introduce the cost and profit systems, the Hausman type (viz., the Shankerman-Nadiri) test for cost minimization and profit maximization behavior, and the LCM/mixture model. Data and results are discussed in Section 3. The final section summarizes the major findings of the paper.

2. The model

2.1 The model with cost minimizing behavior

Here we consider the standard cost function approach[3] that is based on the assumption that producers minimize cost, given output and input prices. In this approach one specifies a cost function and derives the cost share equations (input demand functions) using Shephard's lemma. Usually a translog cost function is chosen to represent the underlying production technology. The corresponding cost system (Christensen and Greene, 1976) is then written as

$$
\begin{aligned}
\ln C_i &= \ln C(\ln p_i, \ln y_i) + v_{1i} \\
S_{1i} &= S_1(\ln p_i, \ln y_i) + v_{2i} \qquad\qquad (1)\\
&\vdots \\
S_{M-1,i} &= S_{M-1}(\ln p_i, \ln y_i) + v_{Mi}
\end{aligned}
$$

where $\ln C_i$ is the log of expenditure, $S_{1i},...,S_{M-1,i}$ denote the $M-1$ cost shares[4], p_i is the $M \times 1$ vector of input prices, y_i is the $Q \times 1$ vector of outputs, and $v_i = [v_{1i},...,v_{Mi}]'$ represents the error terms. The subscript i ($i = 1,...,N$) indicates producers/firms. The above cost system can be estimated using either the seemingly unrelated regression (SUR) technique or the maximum

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[3] Beard, Caudill and Gropper (1991, 1997) considered mixing cost functions to study differences in technology across regimes. They assumed cost minimizing behavior for all observations but allowed the technology to differ across regimes. See also, Caudill (2003), Orea and Kumbhakar (2002) for a stochastic cost frontier application.

[4] One cost share is dropped to avoid the singularity problem.

likelihood (ML) method for which the error vector is assumed to be multivariate normal. That is, $v_i \sim IN_M(0_M, \Omega)$ where Ω is the $M \times M$ covariance matrix. The joint density of the cost system in (1) can then be written as

$$f_{Z_i}(Z_i) = (2\pi)^{-M/2}\left(\det \Omega^{-1}\right)^{1/2} \exp\left(-\tfrac{1}{2} v_i'(Z_i;\theta)\Omega^{-1} v_i(Z_i;\theta)\right) \tag{2}$$

where $Z_i = [\ln C_i, S_{1i}, ..., S_{M-1,i}]'$, and

$v_i(Z_i;\theta) = \left[\ln C_i - \ln C(\ln p_i, \ln y_i), S_{1i} - S_1(\ln p_i, \ln y_i), ..., S_{M-1,i} - S_{M-1}(\ln p_i, \ln y_i)\right]'$.

The maximization with respect to Ω^{-1} can be performed analytically, and substituting its value into (2) yields the following concentrated log-likelihood function

$$\ln L_C(\theta; Z) = -\tfrac{N}{2} \ln[\det(N^{-1} \sum_{i=1}^{N} v_i(Z_i;\theta) v_i(Z_i;\theta)')] \tag{3}$$

which can be maximized to obtain ML estimates of the parameters in the cost system.

2.2 The model with profit maximizing behavior

In the previous section we assumed that producers face exogenously given output and input prices in allocating their inputs to minimize cost. While such an objective is appropriate in some environments, it might be argued that for many producers the ultimate goal is to maximize profit. In such a situation the producers face exogenously given input and output prices (especially when input and output markets are competitive) in their pursuit of allocating inputs and outputs so as to maximize profit. Thus, there is an additional issue of choosing outputs after cost minimizing inputs are chosen. The problem is to find the profit maximizing output quantities. The optimization problem now adds Q additional choice variables – the optimum values of which are to be derived from the following Q additional conditions, viz., $q_j = \partial C / \partial y_j$ ($j = 1,...,Q$) where q_j is the price of output y_j. These conditions (first-order conditions for profit maximization) state that output allocation is optimal when output price equals marginal cost. These equations can be rewritten, in stochastic form, as

$$\ln y_{ji} = \ln C_i - \ln q_{ji} + \ln\left(ey_{ji}(\ln p_i, \ln y_i)\right) + v_{M+j,i}\,,\ j = 1,\dots,Q\,,\ i = 1,\dots,N \qquad (4)$$

where $ey_{ji}(\ln p_i, \ln y_i) = \dfrac{\partial \ln C(\ln p_i, \ln y_i)}{\partial \ln y_{ji}}$ is the output elasticity. Under the behavioral assumption of profit maximization, these additional conditions in (4) are to be appended to the cost system in (1) so that we have a complete system of $M+Q$ equations for $M+Q$ endogenous (choice) variables (M inputs[5] and Q outputs). Another difference with the cost system in (1) is that the present system for a profit maximizing model consisting of (1) and (4) can no longer be estimated using the SUR technique. This is because the endogenous variables (especially outputs) appear on both sides of the equations in (1) and (4). The endogenous variables of the profit system in vector form is

$$\Xi_i = [\ln C_i, S_i', y_i']'$$

where $S_i = [S_{1i},\dots,S_{M-1,i}]'$, and $y_i = [y_{1i},\dots,y_{Qi}]'$ so we have $M+Q$ endogenous variables. Let $v_i = [v_{1i},\dots,v_{M+Q,i}]' \sim IN_{M+Q}\left(0_{M+Q},\Sigma\right)$ where Σ is an $(M+Q)\times(M+Q)$ covariance matrix. Under the assumption of profit maximization, we have a nonlinear simultaneous equation model that can be written in the form

$$f(\Xi_i, \Psi_i; \theta) = v_i\,,\ i = 1,\dots,N$$

where Ψ_i represents the vector of predetermined variables (prices, and possibly other quasi-fixed factors or shift variables) and $\theta \in \Theta \subseteq R^k$ is the parameter vector. The above notation is appropriate for an implicit nonlinear system although in our case we can solve explicitly with respect to Ξ_i.

The joint density function of endogenous variables is

[5] The cost system in (1) treats the cost and (J-1) cost shares as endogenous variables. This is equivalent to treating the inputs as endogenous.

$f_{\Xi_i}(\Xi_i;\theta) = f_{v_i}(v_i(\Xi_i,\Psi_i;\theta)) \cdot | J(\Xi_i,\Psi_i;\theta) |$,

where $| J(\Xi_i,\Psi_i;\theta) | = \left| \left(\frac{\partial v_i(\Xi_i,\Psi_i;\theta))}{\partial \Xi_i} \right) \right|$ is the absolute value of the determinant of the Jacobian of the transformation,

$$f_{v_i}(v_i(\Xi_i)) = (2\pi)^{-(M+Q)/2} \left(\det \Sigma^{-1}\right)^{1/2} \exp\left(-\tfrac{1}{2} v_i'(\Xi_i,\Psi_i;\theta)\Sigma^{-1} v_i(\Xi_i,\Psi_i;\theta)\right),\ i = 1,...,N,$$

and $v_i(\Xi_i,\Psi_i;\theta) \equiv f(\Xi_i,\Psi_i;\theta)$. The Jacobian matrix $J(\Xi_i,\Psi_i;\theta)$ is

$$J(\Xi_i,\Psi_i;\theta) = \frac{\partial v_i(\Xi_i,\Psi_i;\theta)}{\partial \Xi_i} = \begin{bmatrix} 1 & 0'_{M-1} & -ey_i' \\ 0_{M-1} & I_{M\text{-}1} & -\frac{\partial S_i}{\partial \Xi_i} \\ -1_Q & 0'_{Q\times(M-1)} & I_Q - \frac{\partial e_i}{\partial \Xi_i} ey_i^{-1} \end{bmatrix}$$

where $ey_i = diag[ey_{1i},...,ey_{Qi}]'$, $ey_i^{-1} = diag[1/ey_{1i},...,1/ey_{Qi}]'$, and 1_Q is the $Q \times 1$ unit vector.

If the cost function is represented by a single output translog form, namely,

$$\ln C_i = a_0 + \sum_{j=1}^{M} a_j \ln p_{ji} + \tfrac{1}{2} \sum_{j=1}^{M} \sum_{h=1}^{M} a_{jh} \ln p_{ji} \ln p_{hi} + \sum_{j=1}^{M} a_{yj} \ln y_i \ln p_{ji} +$$

$$a_y \ln y_i + \frac{1}{2} a_{yy} (\ln y_i)^2 + a_t t_i + \frac{1}{2} a_{tt} t_i^2 + a_{yt} \ln y_i t_i + \sum_{j=1}^{M} a_{ti} \ln p_{ji} t_i,$$

then $\partial \ln C_i / \partial \ln y_i \equiv ey_i = a_y + a_{yy} \ln y_i + \sum_{j=1}^{M} a_{yj} \ln p_{ji} + a_{yt} t_i$, and $\frac{\partial ey_i}{\partial \ln y_i} = a_{yy}$. Here, t_i represents a trend or, possibly, other variables that shift the cost function. The absolute value of the determinant value of the Jacobian matrix is

$$\left|\det\left(\frac{\partial v_i(\Xi_i,\Psi_i;\theta))}{\partial \Xi_i}\right)\right| = \left|1 - ey_i^{-1}\frac{\partial ey_i}{\partial \Xi_i} - ey_i\right| = \left|1 - ey_i^{-1}a_{yy} - ey_i\right|,\ i = 1,..,N$$

Similar expressions can be derived when there are multiple outputs.

The joint density of endogenous variables is given by

$$f_{\Xi_i}(Y_i;\theta) = (2\pi)^{-(M+Q)/2}\left(\det\Sigma^{-1}\right)^{1/2}\exp\left(-\tfrac{1}{2}v_i'(\Xi_i,\Psi_i;\theta)\Sigma^{-1}v_i(\Xi_i,\Psi_i;\theta)\right)\cdot\left|1 - ey_i^{-1}a_{yy} - ey_i\right|$$

and the log-likelihood function of the system is

$$\ln L(\theta;\Xi,\Psi) = -\tfrac{N(M+Q)}{2}\ln(2\pi) + \tfrac{N}{2}\ln(\det(\Sigma^{-1})) - \tfrac{1}{2}\sum_{i=1}^{N} v_i'(\Xi_i,\Psi_i;\theta)\Sigma^{-1}v_i(\Xi_i,\Psi_i;\theta) + \sum_{i=1}^{N}\ln\left|1 - ey_i^{-1}a_{yy} - ey_i\right| \qquad (5)$$

Maximizing the above log-likelihood function with respect to θ and Σ^{-1} provides the full information maximum likelihood (FIML) parameter estimates. The maximization with respect to Σ^{-1} can be performed analytically, and substituting its value into (5) yields the following concentrated log-likelihood function

$$\ln L_C(\theta;\Xi,\Psi) = -\tfrac{N}{2}\ln[\det(N^{-1}\sum_{i=1}^{N}v_i(Z_i;\theta)v_i(Z_i;\theta)')] + \sum_{i=1}^{N}\ln\left|1 - ey_i^{-1}a_{yy} - ey_i\right|$$

except for the constant term. This function can be maximized using standard numerical techniques.

2.3. Cost minimization or profit maximization?

The models presented in the preceding sections are based on the assumption that producers either minimize cost or maximize profit. The appropriate model can be chosen once the objective of the producers is known. The question is: Do researchers know whether the data at hand comes from producers that are cost minimizers or profit maximizers? This issue can be handled in two ways. First, a formal statistical test might determine whether producers minimize cost or maximize profit. There are different ways to test this hypothesis. Here we follow the test developed by Schankerman and Nadiri (hereafter SN, 1986). Since the cost system in (1) is not nested in the profit system (defined in (1) and (4)) one cannot use a nested test (such as the likelihood ratio test) to find out which model is appropriate for the data. The idea behind the SN test is that under the null hypothesis that producers maximize profit the appropriate model consists of the cost function, the cost share equations (given in (1)) and the first-order conditions of profit maximization (in (4)) which imply $y = y^*$ where y^* is the profit maximizing level of output. Let the parameters in these equations be partitioned as follows

$$\ln C_i = \ln C(\ln p_i, \ln y_i; \beta_0) + v_{1i} \tag{6a}$$

$$S_i = S\ (\ln p_i, \ln y_i; \beta_1) + v_{2i} \tag{6b}$$

$$\ln y_i = \ln C_i - \ln q_i + \ln\left(ey_i(\ln p_i, \ln y_i; \beta_2)\right) + v_{3i} \tag{6c}$$

Further partition the elements of β_0 as $\beta_0 = (\beta_0^0, \beta_2^0)$, where the elements of β_2^0 appear in (6a) and (6c). Under H_0 the restriction $\beta_2 = \beta_2^0$ is in effect. Let $\hat{\beta}$ be the asymptotically efficient, constrained estimator of β from (6a-6c) under the restrictions $\beta_2 = \beta_2^0$, and $\tilde{\beta}$ the unconstrained estimator from (6a-6b) which is consistent under both the null (profit maximization) and alternative hypothesis (cost minimization, i.e., H_1: $y \neq y^*$ meaning that the observed output y is different from the profit maximizing output level, y^*). In order to construct a valid test, $\hat{\beta}$ must be a consistent estimator of β under H_0 but inconsistent under H_1, while $\tilde{\beta}$ must be consistent under both H_0 and H_1. An instrumental variable (IV) estimator is required since y is endogenous under H_0, and appears as regressors in (4). The SN test statistic for H_0 is $R = \sqrt{N}\left(\tilde{\beta} - \hat{\beta}\right)' \hat{V}^{-1}\left(\tilde{\beta} - \hat{\beta}\right) \overset{A}{\sim} \chi_q^2$, where q is the number of restrictions in $\beta_2 = \beta_2^0$, and $\hat{V}$ is a consistent estimator of V.[6] It should be noted that this test is equivalent to the Hausman test for

[6] It is shown in Schankerman and Nadiri (1986) that $\sqrt{N}\left(\tilde{\beta} - \hat{\beta}\right) \overset{A}{\sim} N(0, V)$.

specification error in a system of simultaneous equations. Based on the results of this test, one can decide the appropriate model for the data.

2.4 The latent class model

The main drawback of the test in the previous section is that it does not allow certain producers to be profit maximizers and other producers to be cost minimizers. Consequently, it leads to an overall decision that applies to all producers. Kulatilaka (1985) has developed t-tests that can be used to test the static equilibrium specification by testing for statistical significance of departures between the actual and the optimal long-run levels of quasi-fixed factors. Such tests could be used to test for profit maximization by testing the significance of departures from the first order condition that price equals marginal cost. Here, we explicitly allow for such "departures" as part of the sampling process, and in that way we can also explain why such departures, if any, are observed.

The alternative approach that we adopt here is to assume that every producer is potentially a profit maximizer as well as cost minimizer (with some probability). The probability of being a cost minimizer (profit maximizer) is specified by a logistic function that depends on some exogenous variables. This gives us a finite mixture model where the density of endogenous variables is given by

$$f(\Xi_i;\theta) = \pi_i f_{\Xi_i}(\Xi_i;\theta) + (1-\pi_i) p_{Z_i}(Z_i;\theta)\,,\; i = 1,\ldots,N \qquad (7)$$

where π_i is the probability that the ith firm behaves as if it were profit maximizing. Given a set of predetermined variables, W_i, we parameterize the log-odds ratio in favor of profit maximization as follows:

$$\ln\left(\frac{\pi_i}{1-\pi_i}\right) = W_i'\delta\,,\; i = 1,\ldots,N$$

where $\delta \in \Delta \subseteq R^h$ is a vector of parameters. Therefore, we have

$$\pi_i = \frac{\exp(W_i'\delta)}{1+\exp(W_i'\delta)},\ i = 1,...,N.$$

This parameterization guarantees that π_i is between zero and one, and provides direct interpretation of δ. Finite mixture or latent class models are well established in statistics and econometrics and have been used widely in applications, see for example the comprehensive monograph by Titterington, Smith, and Makov (1985), and Greene (2002) for some recent applications.

Based on (7) we can formulate the log-likelihood function

$$\ln L(\theta, \Sigma^{-1}, \Omega^{-1}, \delta; \Xi, \Psi, W) = \sum_{i=1}^{N} \ln\left[\pi_i f_{\Xi_i}(\Xi_i;\theta) + (1-\pi_i) p_{Z_i}(Z_i;\theta)\right]$$

We can maximize this function to obtain FIML estimates of all parameters. Straightforward application of Bayes' theorem yields an estimate of the posterior probability that the ith firm maximizes profit:

$$\widetilde{Q}_i = \frac{\pi_i\left(\widetilde{\delta}\right) f_{\Xi_i}(\Xi_i;\widetilde{\theta})}{\pi_i\left(\widetilde{\delta}\right) f_{\Xi_i}(\Xi_i;\widetilde{\theta}) + \left(1-\pi_i\left(\widetilde{\delta}\right)\right) p_{Z_i}(Z_i;\widetilde{\theta})},\ i = 1,...,N,$$

where the FIML estimates were substituted for θ and δ, and $\pi_i\left(\widetilde{\delta}\right) \equiv \frac{\exp\left(W_i'\widetilde{\delta}\right)}{1+\exp\left(W_i'\widetilde{\delta}\right)}$, $i = 1,...,N$.

These posterior probabilities are firm-specific even when π_i is a parameter. Clearly, the estimated posterior probabilities summarize all the evidence for or against profit maximization. Ideally, we would like to have Q_i equal to either zero or one (or nearly so) so that the choice in favor or against profit maximization is more or less clear. Empirically, we cannot always expect that, and Q_i could be anywhere between these limits. In such cases, one could say that a firm is likely to be profit maximizing provided $\widetilde{Q}_i > \frac{1}{2}$.

3. Data and results

To illustrate the technique proposed in the preceding sections, we use an unbalanced panel data set[7] consisting of annual observations on the domestic operations of 23 US airlines over the period 1971-1986. A total of 268 observations are used here. Variable inputs are labor (L), materials (M) and fuel (F). Capital (K) it treated as a quasi-fixed factor. To control for firm-heterogeneity, we also include 22 airline dummies in the cost function.

Maximizing the likelihood function given by the mixture model is an involved procedure primarily because it is not possible to concentrate with respect to Σ^{-1} and Ω^{-1}. These matrices contribute $\frac{1}{2}\left[M(M+1)+(M+Q)(M+Q+1)\right]$ parameters. When $M=3$ and $Q=1$ we have 16 nuisance parameters. To guarantee that Σ and Ω represent positive definite covariance matrices we use a Cholesky decomposition, namely, $\Sigma^{-1}=A'A$ and $\Omega^{-1}=C'C$ where A and C are, respectively, $M\times M$ and $(M+Q)\times(M+Q)$ upper triangular matrices. We treat the elements of A and C (on and above the diagonal) as parameters.

We report the SN test results for overall profit maximization in Table 2. We performed several such tests depending on instruments used and whether heterogeneity in the cost function (by including airline dummies in the cost function) is taken into account or not. To implement the SN test, we use the 3SLS estimators from two systems. The first one is obtained from the standard cost system, and the second one is from the profit system (consisting of the cost system plus the additional equation derived from the profit maximizing behavior, viz., p = MC). The results of the SN tests do not support overall profit maximization behavior. Unfortunately, this is an overall test that does not provide further information regarding which airlines are maximizing profit and which are not.

[7] For details regarding the data, see Appendix A of Baltagi, Griffin and Vadali (1998).

Next, we turn our attention to results obtained from the cost minimizing model (CMM), the profit maximizing model (PMM), and the LCM. Parameter estimates from these models, along with their asymptotic t-statistics[8], are reported in Table 1. To estimate the CMM we maximize the likelihood function using the OLS estimates of the cost function as the starting values. To estimate the PMM we use the FIML method starting from the cost system (non-linear SUR) estimates. Finally, to estimate the LCM we use FIML technique in which the simple average of estimates obtained from the cost minimizing and profit maximizing models are used as the starting values.

We used 24 variables, *viz*., a constant term, a deregulation dummy (that separates observations before and after airlines deregulation in 1978) and 22 airline dummy variables to capture heterogeneity in profit maximizing behavior. From the estimated coefficients in the log-odds equation (reported in Table 2), we can see that (i) all the coefficients are statistically significant, (ii) deregulation has a statistically significant and positive impact upon the odds in favor of profit maximization, and (iii) airlines seem to differ substantially in their individual log-odds in favor of profit maximization. Only one airline (North West) seems to stand out in terms of having positive coefficients associated with its dummy variable (indicating substantially higher log-odds relative to the rest).

In Table 3.1, we report sample averages and sample standard deviations of scale economies and technical change. Mean values of scale economies are 0.56, 1.037 and 0.552 for the CMM, the PMM and the LCM, respectively, with standard deviations 0.06, 0.301, and 0.130. Therefore, the models (especially the PMM) have very different implications in terms of scale economies. Since the SN test rejects the overall profit maximizing behavior, results from the PMM that impose profit maximizing behavior might be misleading. This is especially the case if one looks at the correlation coefficient of scale economies obtained from the PMM and the CMM (LCM). The correlations (reported in Table 3.2) are quite high. The mean technical change corresponding to the CMM, PMM and LCM are -0.029, -0.036, and -0.028, respectively, with standard deviations 0.005, 0.003, and 0.001. Thus, on average technical progress at the rate

8 Standard errors are obtained from the inverse Hessian of the log-likelihood function.

of 2.8% to 3.6% per annum is predicted by these models. Although the mean technical change from the PMM is not very different from the other two models, the correlation coefficients of technical change obtained from the PMM and the CMM (as well as the LCM) is found be negative (Table 3.3). To focus more on these differences, kernel density estimates of airline-specific measures of scale economies and technical change are reported in Figures 1 - 4, before and after deregulation. Deregulation is not found to have a large impact upon these measures but differences across models seem to be substantial. We believe that the LCM gives the most reliable estimates of scale economies and technical change. This is because the LCM allows us to estimate the same technology irrespective of whether an airline maximizes profit or minimizes cost. In other words, the LCM can impose the constraint of common technology irrespective of behavioral assumptions.

From estimated posterior probabilities only the following observations seem to favor profit maximization behavioral assumption: BR (1981), CN (1984-1986), ML (1982-1986), NW (1972-1986), PA (1986), PO (1986), and WN. Clearly, only NW and WN consistently behaved like profit maximizers. In Figure 5, we report histograms of the prior probability of profit maximization (upper left panel), the posterior probability (upper right panel), and posterior probability before and after deregulation (lower panels). The prior probability average is 0.12 with the sample standard deviation of 0.30. The median is very close to zero (0.0005) and the 75% and 90% quantiles are 0.0011 and 0.423, respectively. The posterior probabilities leave little doubt that airlines are not profit maximizers. The posterior probabilities are, fortunately, very sharp (either very close to zero or unity), and are close to unity for about 10% of airlines. Clearly, the posterior probability in favor of profit maximizing behavior increases somewhat (from about 8% to 15%) after the deregulation but the bulk of airlines remains to be cost minimizers. Thus, we don't have clear evidence that deregulation changed economic behavior of the airlines, viz., from cost minimization to profit maximization.

4. Conclusions

In this paper we proposed a latent class model (LCM) to determine whether firms behave like profit maximizers or cost minimizers when there is no additional sample separation information. Existing econometric tests (e.g., Schankerman and Nadiri, 1989) allowed us to test for profit maximization. These tests, however, give an overall conclusion either in favor or against profit maximization for all firms in the sample. In practice some firms might be maximizing profit while others might minimize cost. The researchers may not have any information on which firms maximize profit. In such a situation the LCM is quite useful. Estimation of the LCM amounts to mixing a seemingly unrelated regression model (resulting from cost minimization) with a simultaneous equation model (the cost minimizing system plus the equality of marginal costs and output prices) with cross-equation and cross-model restrictions in such a way that the technology is the same for all firms irrespective of their behavioral assumptions. The log-odds ratio in favor of profit maximization is parameterized in terms of predetermined variables. Estimates of this function are used to predict the posterior probability of firms maximizing profit or minimizing cost. The LCM is estimated using panel data on a sample of U.S. airlines. We find that deregulation helped somewhat but only about 15% of the airlines are found to be consistent with profit maximizing behavior. In other words, we don't find evidence that all airlines were maximixing profit, especially after deregulation in 1978.

Table 1: Parameter estimates from alternative models

Model	Cost Min.		Profit Max.		Mixing	
Parameter	**Est**	**Std err**	**Est**	**Std err**	**Est**	**Std err**
Const.	7.494	0.215	7.366	0.210	6.929	0.134
$\ln(p_1)$	0.735	0.056	0.695	0.056	0.540	0.042
$\ln(p_2)$	-0.611	0.070	-0.607	0.068	-0.409	0.045
$\ln(k)$	0.311	0.124	-0.585	0.134	-0.028	0.008
$\ln(y)$	0.691	0.108	1.529	0.125	0.901	0.062
t	-0.061	0.006	-0.061	0.007	-0.047	0.005
$\ln(p_1).\ln(p_1)$	0.139	0.011	0.131	0.011	0.056	0.072
$\ln(p_1).\ln(p_2)$	-0.046	0.010	-0.046	0.010	0.093	0.009
$\ln(p_2).\ln(p_2)$	0.138	0.012	0.137	0.012	-0.009	0.008
$\ln(k).\ln(k)$	-0.369	0.209	-2.082	0.095	0.102	0.008
$\ln(y).\ln(y)$	-0.166	0.176	-1.508	0.065	-0.982	0.087
$t.t$	0.001	0.001	-0.001	0.001	-0.625	0.073
$\ln(p_1).\ln(k)$	0.083	0.013	-0.080	0.026	0.000	0.000
$\ln(p_2).\ln(k)$	-0.027	0.009	-0.042	0.021	0.089	0.009
$\ln(p_1).\ln(y)$	-0.070	0.011	0.088	0.024	-0.077	0.008
$\ln(p_2).\ln(y)$	0.012	0.008	0.028	0.020	0.015	0.007
$\ln(p_1).t$	-0.003	0.001	-0.005	0.001	-0.001	0.001
$\ln(p_2).t$	0.004	0.001	0.004	0.001	0.003	0.001
$\ln(k).\ln(y)$	0.241	0.187	1.770	0.074	0.765	0.075
$\ln(k).t$	0.006	0.006	-0.018	0.004	0.002	0.004
$\ln(y).t$	-0.006	0.005	0.016	0.004	-0.002	0.004

Table 2: Parameter estimates of the log-odds function

Parameter	Estimate	Std err
Constant	-23.571	0.181
Deregulation	26.445	0.181
D1	-10.014	0.193
D2	-10.563	0.193
D3	-3.627	0.191
D4	-3.185	0.188
D5	-10.542	0.193
D6	-10.475	0.193
D7	-9.913	0.193
D8	6.058	0.193
D9	-7.291	0.193
D10	-4.915	0.193
D11	59.564	0.193
D12	-9.681	0.193
D13	-4.197	0.189
D14	-4.787	0.190
D15	-9.623	0.193
D16	-10.269	0.193
D17	-7.370	0.193
D18	-3.925	0.193
D19	-8.605	0.193
D20	-10.563	0.193
D21	-10.544	0.193
D22	-10.242	0.193

Table 3. 1. Scale economies and technical progress across models

	CMM	PMM	LCM
Scale economies	0.56 (0.06)	1.037 (0.301)	0.552 (0.130)
Technical change	-0.029 (0.005)	-0.036 (0.003)	-0.028 (0.001)

Notes: Sample means are reported. Sample standard deviations appear in parentheses.

Table 3. 2. Correlation coefficients of scale economies across models

	Cost min.	**Profit max.**	**Mixing**
Cost min.	1	0.633	0.823
Profit max.		1	0.945
Mixing			1

Table 3. 3. Correlation coefficients of technical change across models

	Cost min.	**Profit max.**	**Mixing**
Cost min.	1	-0.293	0.847
Profit max.		1	-0.363
Mixing			1

Table 4. The Schankerman-Nadiri test results

	Specification			Test	p-value
	Dummies in cost function?	Dummies as instruments?	Deregulation and interactions as instruments?		
1	yes	yes	no	67.659	0.000
2	no	yes	no	144.43	0.000
3	no	no	no	19.798	0.0014
4	yes	yes	yes	71.052	0.000
5	no	yes	yes	191.792	0.000
6	no	no	yes	59.629	0.000

Notes: The Schankerman-Nadiri tests were computed as follows. Under the null of profit maximization, the 3SLS estimator of cost-share system plus the profit maximization condition is efficient. The 3SLS estimator of the cost-share system is consistent under the null as well as under the alternative that profit maximization does not hold. So the test is a Hausman specification test. The lists of instruments vary across the different cases we consider. The basic set is log prices, log capital stock, the time trend, their squares, and their cross-products. There are 22 airline-specific dummy variables. Interactions of the deregulation dummy were taken with the variables in the basic instrument set.

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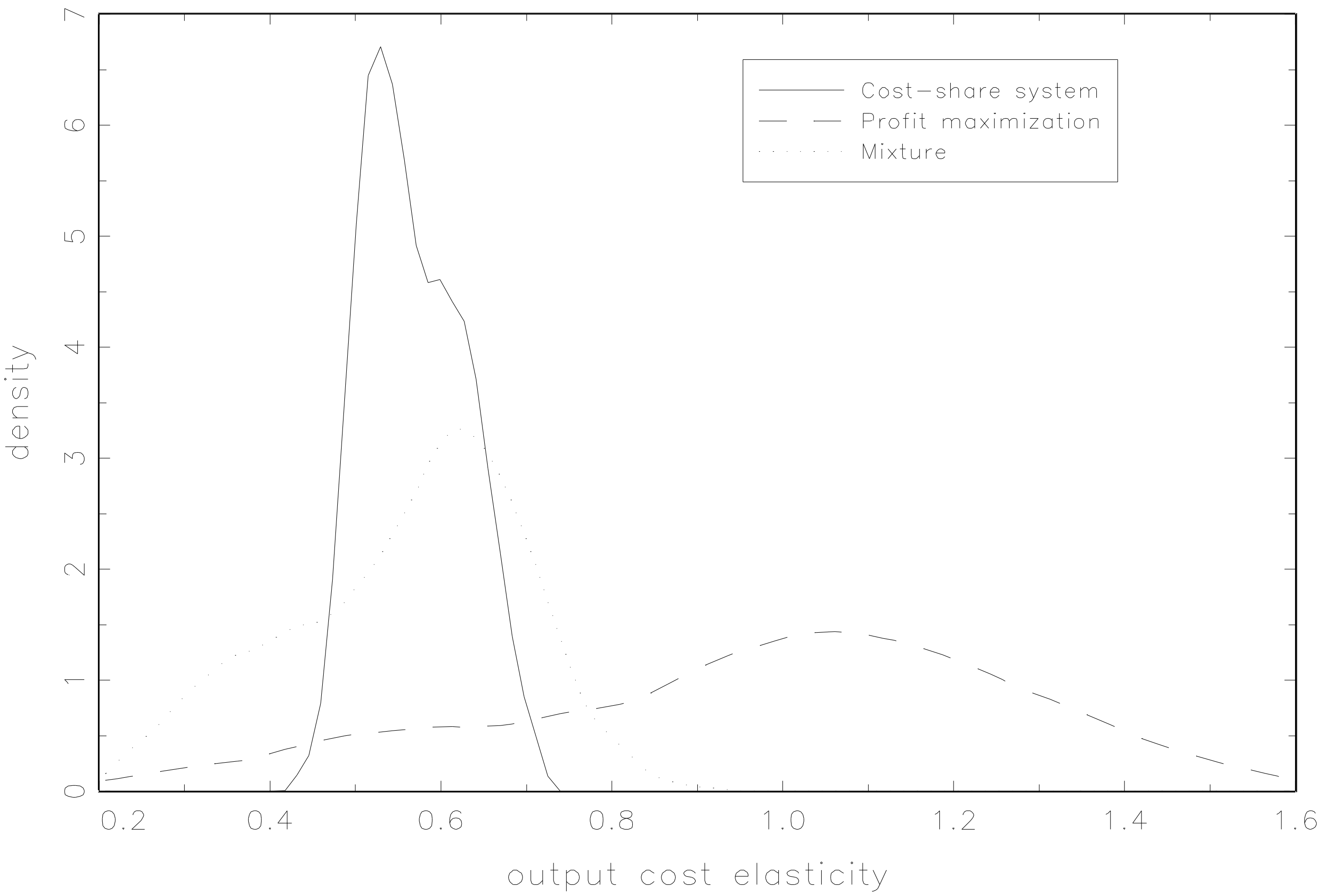
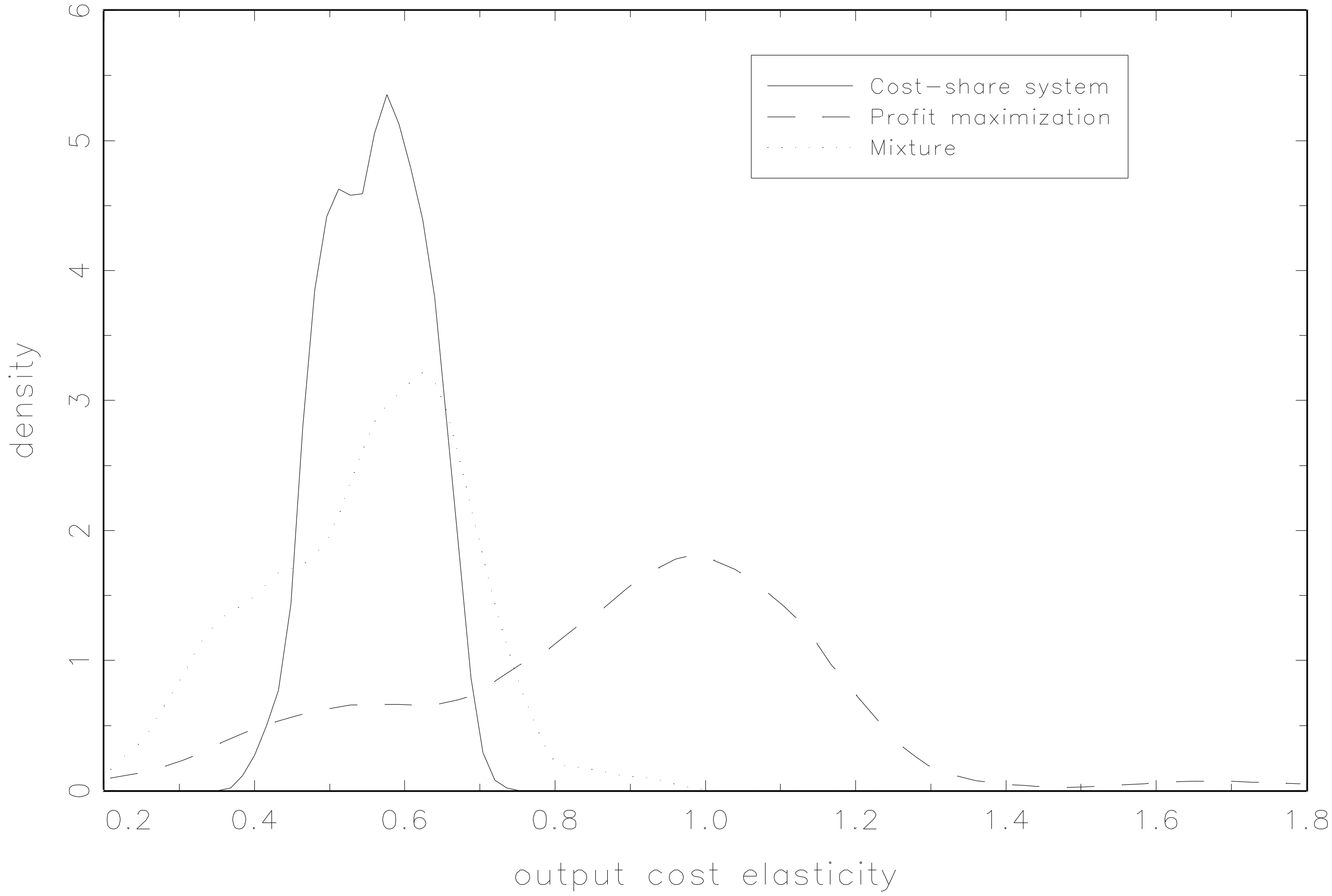
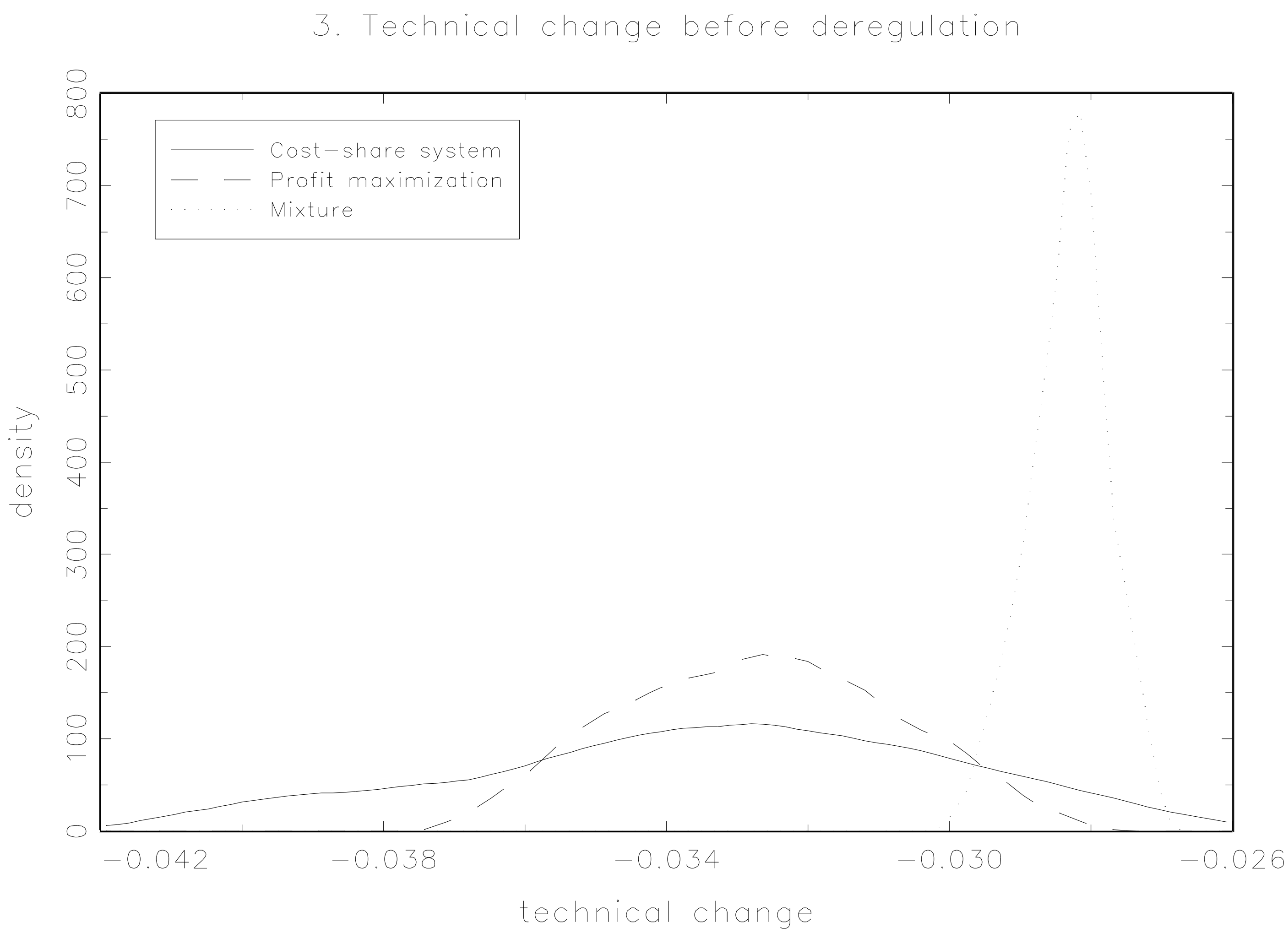
1. Output cost elasticity before deregulation

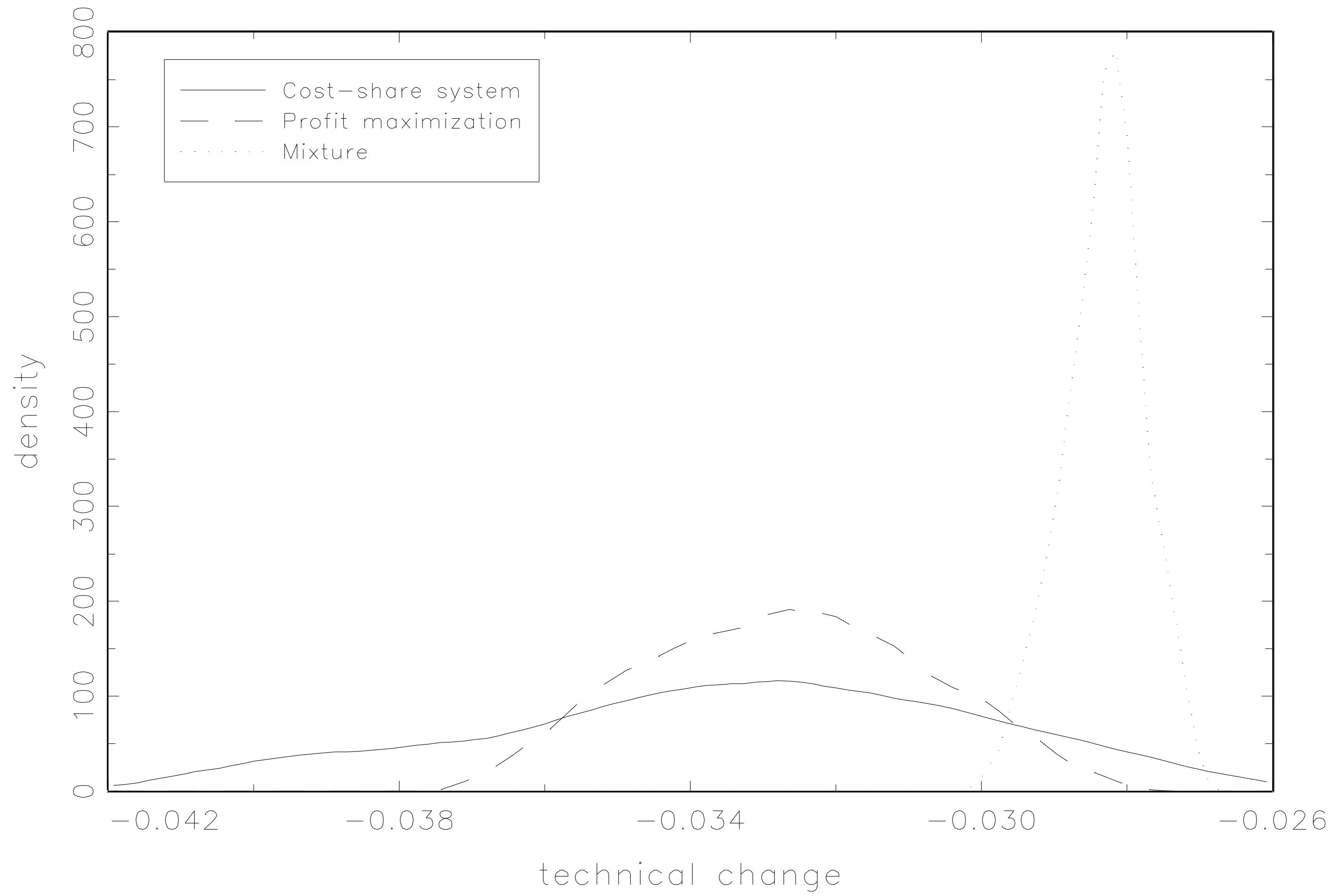


2. Output cost elasticity after deregulation

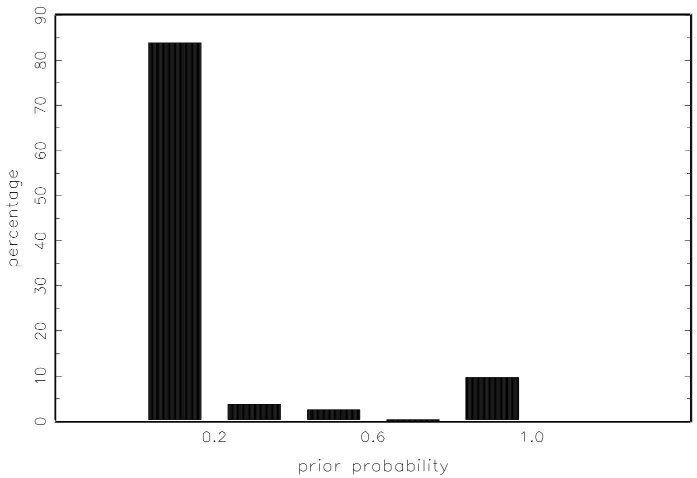



3. Technical change before deregulation
Cost-share system
Profit maximization
Mixture
density
0
100
200
300
400
500
600
700
800
−0.042
−0.038
−0.034
−0.030
−0.026
technical change

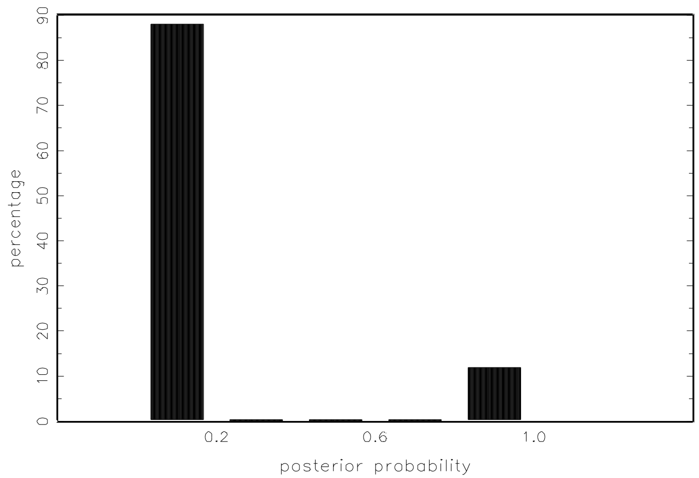
4. Technical change after deregulation



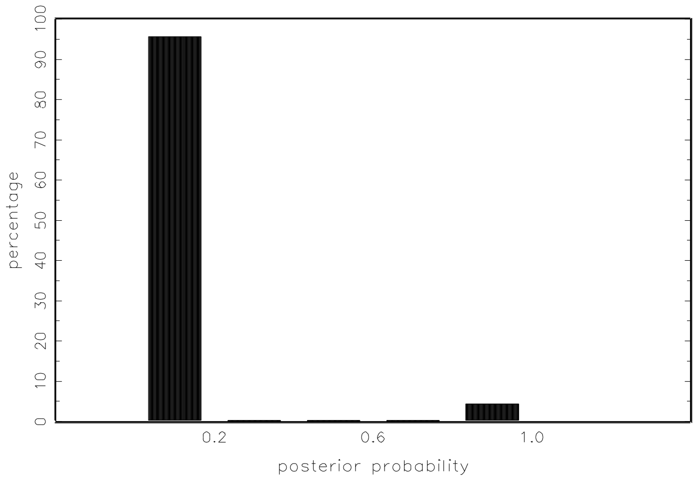
5a. Prior probability of profit maximization



5b. Overall posterior probability of profit maximization



5c. Posterior probability before deregulation



5d. Posterior probability after deregulation