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INFERRING TECHNOLOGICAL PARAMETERS FROM INCOMPLETE PANEL DATA

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RÉSUMÉ

Cet article présente une méthode d'estimation des fonctions de coût et de demande de facteurs des entreprises avec données de panel incomplètes. La plupart des panels sont incomplets pour différentes raisons: fusions, acquisitions de filiales, banqueroutes, données d'enquêtes incomplètes, etc. Lorsqu'une entreprise est absente pour au moins une période, toutes ses données sont manquantes durant ces périodes. Notre méthode estime simultanément le système fonction de coût-demande de facteurs et un modèle probit de sortie de l'échantillon avant la dernière année de la période étudiée. L'entrée dans l'échantillon après la première période n'est pas modélisée explicitement comme la sortie, mais considérée comme étant exogène. Pour tenir compte de l'aspect panel des données, des effets aléatoires spécifiques aux entreprises ont été introduits dans les modèles de coûts et de sélection, ce qui rend leur estimation jointe très difficile. Conséquemment, des restrictions ont été imposées sur les variables aléatoires pour simplifier l'analyse. Par exemple, nous avons supposé que les variances et covariances des termes d'erreurs sont constantes dans le temps. Malgré ces hypothèses, l'estimation des modèles demeure délicate et oblige l'utilisation de techniques d'intégration numérique. La méthode a été appliquée à un panel incomplet d'entreprises de camionnage ontariennes durant la période 1981–1988. Les estimations indiquent que la sortie est endogène, ce qui aurait entraîné des estimations biaisées des paramètres et des écarts types si les corrections appropriées n'avaient pas été apportées. Finalement, nous montrons comment la spécification de la fonction de coût peut affecter les résultats.

Mots-clés : panel incomplet, entrée, sortie, fonction de coût, fonctions de demande de facteurs, paramètres technologiques.

ABSTRACT

This paper presents a method for the estimation of cost and input demand functions with incomplete panel data. Most panel data sets of firms actually available are incomplete for numerous reasons: mergers, acquisitions, bankruptcies, incomplete surveys, etc. Hence, in this type of sample, when a firm is missing for at least one period, all the variables relevant to this firm are missing in the same periods. Our method jointly considers the cost-input demand system and a probit selection model of exit from the sample before the end of the period under study. Entry into the sample after the first period is not explicitly modelled as exit, but rather, is considered as exogenous. In order to take into account of the panel aspect of the data, random firm-specific effects were included in both the cost and selection models. The inclusion of random effects in the models makes their joint estimation much more difficult. However, some restrictions have been imposed on the random variables in order to simplify the analysis. For instance, we assumed that the variances and covariances of the error terms are constant over time. Nevertheless, the estimation is quite delicate since it relies on numerical integration. The method was applied to an incomplete panel of Ontario trucking firms from 1981 to 1988. Estimations indicate the presence of endogenous exit which would have resulted in biased parameter and standard error estimates without appropriate correction. Finally, we show how the specification of the cost function affects de results.

Keywords : Incomplete panel data, entry, exit, cost function, input demand functions, technological parameters. — JEL CODES : C33, C51, D24

1. Introduction

Over the last two decades, important developments have been made in the so-called field of "production economics". Technological parameters such as returns to scale, elasticities of substitution and technical change are now commonly computed from cost function estimates, applying duality principles. The development of flexible functional forms, such as the translog by Christensen, Jorgensen and Lau (1971, 1973) for instance, made possible the inference of the technological structure of a firm or an industry without any a priori restrictions.[1]

These functional forms approximate the cost function and may be estimated using three types of data: i) time-series data on a single firm or industrial sector; ii) a cross-section over several firms or sectors at a point in time; iii) a panel data set. In most cases, a panel data set is preferred to a time-series or a cross-sectional data set because it brings more degrees of freedom, and also permits the inference of technological parameters without any strong restrictions.[2]

While the benefits of using panel data are certainly greater than the costs, these costs should not be underestimated. With panel data, care must be taken in specifying the equations to be estimated in order to take into account the particular structure of the error terms. Time- and firm-specific effects must be included in the econometric model. Specific effects can be considered as fixed or random. These aspects of the econometrics of panel data are well documented in a literature which is still growing.[3]

Another aspect of panel data which has received little attention is that most (if not all) panel data sets are incomplete; that is, some firms are not in the sample for the entire period

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[1] See Diewert and Wales (1987) for a formal definition of a flexible functional form.

[2] For instance, technical change cannot be estimated with cross-sectional data but can be with time-series or panel data. However, the estimation of technical change with time-series must be done assuming a constant rate of growth. With panel data, the evolution of estimated technical change may be irregular. Baltagi and Griffin (1988) present an econometric model for the estimation of technical change showing irregular patterns with panel data.

[3] See, for instance, Hsiao (1986) and Mátyás and Sevestre (1993).

under study. Observations on firms may be missing for several reasons, including non-response to the survey, not surveyed, merger, acquisition, bankruptcy, etc. On the one hand, if firms are randomly missing no real problem arises and the cost function may be estimated with the incomplete panel data set as if it were complete. On the other hand, if firms are missing for certain specific reasons which are not independent of the determinants of the cost function, estimation of the cost model without an appropriate correction may cause selection bias. The case where the panel is incomplete because of missing variables for some firms or individuals has received more attention, especially in the literature on labor economics. Hausman and Wise (1979) developed a two-period panel model where the earnings for some individuals are only observed in the first period. Later, Keane, Moffitt and Runkle (1988) used a maximum likelihood procedure to estimate a wage equation with an incomplete panel data set of workers covering a period of 12 years.

In this paper, we use an approach related to that of Keane, Moffitt and Runkle (1988). However, instead of one outcome equation (wage), we have four outcome equations (cost and input shares) which increase the complexity of the estimation procedure. Furthermore, the selectivity problem is taken into account by an exit equation jointly estimated with the outcome model (cost and input shares). Entry into the panel after the first period is treated as exogenous, but entering firms may differ from the others since an entry dummy variable is included in the cost function.

Our econometric model considers a cost function approximated by a translog form and its corresponding input share equations. Besides output and input prices, the specification of the cost function also includes technological characteristics taking into account output heterogeneity and network attributes. For the estimation, we distinguish four types of firms: i) those in the panel over the entire period under study; ii) those exiting the panel before the end of the period; iii) those entering the panel after the first period; and iv) those entering after the first period and leaving before the last. Random firm-specific effects and fixed time effects are both included in the cost and exit equations in order to control for the panel aspect of the data. The complete model (cost, input shares and exit equations) is estimated by maximum likelihood. In order to make the optimization of the likelihood function tractable, restrictions are imposed on the random variables. For instance, we assume that the variances and covariances of the error terms are constant over time.

The rest of the paper is organized as follows. In section 2 we present the cost model and its translog approximation, and we also define key technological measures. Section 3 gives a detailed discussion of the econometric model, particularly the error structure (random effects) and the implementation of the exit equation. An application of the methodology to the Ontario trucking industry is presented in section 4, while section 5 gives a short conclusion.

2. The Cost Model

The estimation of cost and input demand functions is now recognized as the most appropriate method for the inference of technological parameters such as returns to scale, technical change and elasticities of substitution. This approach assumes a production function of the form:[4]

$$y_{it} = F(\mathbf{x}_{it}, \mathbf{q}_{it}, A_t), \tag{1}$$

where y_{it} is the level of output of firm i at period t, $\mathbf{x}_{it}$ is a vector of input quantities $(x_{1it}, ..., x_{mit}, ..., x_{Mit})$, $\mathbf{q}_{it}$ is a vector of technological characteristics $(q_{1it}, ..., q_{uit}, ..., q_{Uit})$. A_t is an index of technological change which represents the state of the technology in the industry. F is at least twice continuously differentiable, increasing and concave in $\mathbf{x}_{it}$. The vector of technological characteristics may include variables taking into account the heterogeneity of the output (such as different qualities) and the particular conditions under which firms are operating (for instance, variables measuring the network attributes of transportation firms).

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[4] A multiproduct technology could also be considered.

If firms are cost minimizing, there exists a cost function dual to the production function. This cost function gives the minimum cost of producing y_{it}, given the input prices $\mathbf{w}_{it}=(w_{1it}, \ldots, w_{mit}, \ldots, w_{Mit})$, the characteristics $\mathbf{q}_{it}$ and the state of the technology A_t, i.e.:[5]

$$C(y_{it}, \mathbf{w}_{it}, \mathbf{q}_{it}, A_t) \equiv \min_{x_{mit}} \left\{ \sum_{m=1}^{M} w_{mit}\, x_{mit} : y_{it} = F(\mathbf{x}_{it}, \mathbf{q}_{it}, A_t) \right\}. \tag{2}$$

The cost function $C(y_{it}, \mathbf{w}_{it}, \mathbf{q}_{it}, A_t)$ is increasing in y_{it} and $\mathbf{w}_{it}$, homogeneous of degree one, and concave in $\mathbf{w}_{it}$.

To estimate the above cost function, we must assume a specific functional form for it. Since we do not have any a priori knowledge of the technology represented by the production function (1), $C(y_{it}, \mathbf{w}_{it}, \mathbf{q}_{it}, A_t)$ can be approximated by a translog form (Christensen, Jorgenson and Lau, 1973) which represents a second-order Taylor series approximation of an unknown function. The translog form is the most widely used approximation in applied works and a Monte-Carlo study showed that it is still the best form available for technological measurements (Gagné and Ouellette, 1994).

The index of technical change included in the cost function is not observable in most cases. Therefore, following Baltagi and Griffin (1988), the index of technical change is considered a parameter to be estimated.[6] Because it is different for each period, it must be estimated using a panel data set of firms. Moreover, the number of firms in the panel for each period t must be large enough to get consistent estimates of A_t $(t = 1, \ldots, T)$.

The translog approximation of $C(y_{it}, \mathbf{w}_{it}, \mathbf{q}_{it}, A_t)$ is given by:

$$\begin{aligned} \ell n(C_{it}) &= \mathbf{a}_o + A_t + (b_y + \phi_y A_t)\tilde{y}_{it} \\ &\quad + \sum_{m=1}^{M} (c_m + \psi_m A_t)\tilde{w}_{mit} \end{aligned}$$

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[5] This is a long-term cost function. A short-term function can also be specified.

[6] The specification of Baltagi and Griffin (1988) did not consider technological characteristics ($\mathbf{q}_{it}$).

$$
\begin{aligned}
&+\sum_{u=1}^{U}(d_u+\mu_u A_t)\tilde{q}_{uit}\\
&+\tfrac{1}{2}\,\mathrm{b}_{yy}\;\tilde{y}_{it}^2\\
&+\tfrac{1}{2}\sum_{m=1}^{M}\sum_{s=1}^{M} c_{ms}\;\tilde{w}_{mit}\tilde{w}_{sit}\\
&+\tfrac{1}{2}\sum_{u=1}^{U}\sum_{v=1}^{U} d_{uv}\;\tilde{q}_{uit}\tilde{q}_{vit}\\
&+\sum_{m=1}^{M} f_{ym}\;\tilde{y}_{it}\tilde{w}_{mit}\\
&+\sum_{u=1}^{U} g_{yu}\;\tilde{y}_{it}\tilde{q}_{uit}\\
&+\sum_{m=1}^{M}\sum_{u=1}^{U} h_{mu}\;\tilde{w}_{mit}\tilde{q}_{uit}, \qquad (3)
\end{aligned}
$$

where C_{it} represents total costs, $\hat{z} \equiv \ell n(z/\bar{z})$ and $\bar{z}$ is the sample mean of z. The $A_t (t = 1, \ldots, T)$ are estimated using the appropriate time dummy variables and by setting $A_1 = 0$. Homogeneity of degree one is imposed by dividing total costs (C_{it}) and $M - 1$ input prices (w_{mit}) by w_{Mit}. Also, the following symmetry restrictions are imposed on (3) prior to its estimation:

$$
\begin{aligned}
c_{ms} &= c_{sm} \quad \text{for } s, m = 1, \ldots, M-1,\\
d_{uv} &= d_{vu} \quad \text{for } u, v = 1, \ldots, U. \qquad (4)
\end{aligned}
$$

Using Shephard's lemma, the input share equations corresponding to (3) are:

$$S_{mit} \;= c_m + v_m A_t + \sum_{s=1}^{\mathrm{M}-1} c_{ms}\;\hat{w}_{sit} + f_{ym}\;\hat{y}_{it} + \sum_{u=1}^{U} h_{mu}\hat{q}_{uit}.\; m = 1, \ldots, M, \qquad (5)$$

where S_{mit} is the cost share of input m. The usual procedure is to add disturbances to equations (3) and (5) and jointly estimate the cost function and its corresponding input share equations. However, since input shares add up to 1, an input share equation must be deleted in order to avoid the singularity of the estimated disturbance covariance matrix. Results are independent of the share deleted if they converge to maximum likelihood estimates (Barten, 1969).

Using the parameter values obtained from the estimation of the model defined by (3), (4) and (5), returns to scale may be computed as:

$$RTS_{it} = 1/\epsilon_{it}, \tag{6}$$

where ϵ_{it} is the elasticity of cost with respect to output and is computed as:

$$\epsilon_{it} = b_y + \phi_y A_t + b_{yy}\,\tilde{y}_{it} + \sum_{m=1}^{M-1} f_{ym}\,\tilde{w}_{mit} + \sum_{u=1}^{U} g_{yu}\,\tilde{q}_{uit}. \tag{7}$$

Firm i is operating under constant (decreasing or increasing) returns to scale at period t when $RTS_{it} = 1 (RTS_{it} < 1$ or $RTS_{it} > 1)$.

Analogously, the estimated rate of technical change is computed by:[7]

$$\dot{T}_{it} = -\left(\frac{1 + \phi_y\,\tilde{y}_{it} + \sum\limits_{m=1}^{M-1} \psi_m\,\tilde{w}_{mit} + \sum\limits_{u=1}^{U} \mu_u\,\tilde{q}_{uit}}{\epsilon_{it}}\right)(A_t - A_{t-1}). \tag{8}$$

The estimated rate of technical change computed by equation (8) can be decomposed into four different components: 1) pure technical change $(-(A_t - A_{t-1})/\epsilon_{it})$; 2) scale-biased technical change $(-(\phi_y\tilde{y}_{it})(A_t - A_{t-1})/\epsilon_{it})$; 3) input-biased technical change $\left(-\left(\sum\limits_{m=1}^{M-1} \psi_m\tilde{w}_{mit}\right)(A_t - A_{t-1})/\epsilon_{it}\right)$; and 4) quality- or network-biased technical change $\left(\left(-\sum\limits_{u=1}^{U} \mu_u\tilde{q}_{uit}\right)(A_t - A_{t-1})/\epsilon_{it}\right)$.

Finally, the estimated Allen elasticity of substitution between inputs m and s $(m \neq s)$ is defined as:

$$\rho_{it}^{ms} = \frac{C_{it}\Delta_{it}^{ms}}{x_{mit}x_{sit}}, \tag{9.1}$$

where C_{it} represents the total cost for firm i at time t; x_{mit}, x_{sit} represent the quantity of inputs m and s, and Δ_{it}^{ms} is the second partial derivative of the cost function with respect to inputs m and s evaluated at each point (i, t).[8] A larger ρ means a higher degree of substitutability

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[7] See Denny, Fuss and Waverman (1981) for an elaborate discussion of technical change and its related aspects, and see also Dionne and Gagné (1992) on the estimation of technical change using incomplete panel data with exogenous exit.

[8] From (3), Δ_{it}^{ms} is computed as: $\frac{C_{it}}{w_{mit}w_{sit}}[c_{ms} + S_{mit}S_{sit}]$.

between inputs m and s. In the case of the translog form defined by equation (3), the Allen elasticity of substitution is computed as:

$$\rho_{it}^{ms} = \frac{c_{ms} + \hat{S}_{mit}\hat{S}_{sit}}{\hat{S}_{mit}\hat{S}_{sit}}, \tag{9.2}$$

where $\hat{S}_{mit}$ and $\hat{S}_{sit}$ represent the fitted share of inputs m and s for firm i at time t.

3. An Econometric Model for Incomplete Panels

In order to get consistent estimates of the A_t, the cost model described above must be estimated with a panel where the number of firms (N) is sufficiently large. On the other hand, with this type of specification, the number of periods (T) could be as small as two, but could also be very large. However, panels for which N is large are likely to be incomplete. The higher the number of firms considered in the analysis, the higher the probability that some of them may exit the sample before the end of the period under study. Also, some firms may enter the sample after the first period. In practice, most (if not all) panel data sets of firms are incomplete, and neglecting this particular aspect of a panel may potentially introduce selection bias.

Let us consider the cost model described above, to which we add disturbances. The model may be written compactly as:

$$\ell n(C_{it}) = \ell n\, C(y_{it}, \mathbf{w}_{it}, \mathbf{q}_{it}, A_t) + u_{it}, \tag{10.1}$$

$$S_{mit} = S_m(y_{it}, \mathbf{w}_{it}, \mathbf{q}_{it}, A_t) + \omega_{mit}, \;\; m = 1, ..., M-1, \tag{10.2}$$

where S_{mit} is the observed share of input m, $E(u_{it}, \omega_{1it}, ..., \omega_{M-1it}) = 0$ and $Var(u_{it}, \omega_{1it}, ..., \omega_{M-1it}) = \sum_{u\omega}$. With complete panels, equations 10.1 and 10.2 can be jointly estimated by the nonlinear seemingly unrelated regression (NSURE) method (Gallant and Jorgenson, 1979). Also, estimates obtained from iterative NSURE will converge to maximum likelihood estimates.

In this paper, we address the following question: if entry after the first period or exit before the last occur in the panel, could equations 10.1 and 10.2 be estimated by NSURE? The answer is no if entry to or exit from the sample is correlated with the determinants of the cost model. In that case, firms are neither randomly nor exogenously missing, and estimation by standard methods such as NSURE may lead to biased results.

To illustrate this, let us first consider exit from the sample. A firm may exit the sample before the end of the period under study for several reasons, including non-response to the survey, merger, acquisition, bankruptcy, and not being always surveyed. In some of these cases, exit may be considered as random or at least exogenous but, in general, the analyst doing the study only observes that a firm is exiting the sample, not the reason why it is exiting. In such circumstances, it is necessary for the estimation to consider the potential correlation between the determinants of the cost and those of exit from the sample.

The endogeneity of exit may be taken into account with the following exit model where $d_{it} = 1$ if firm i is exiting the sample at period t ($d_{it} = 0$, otherwise):

$$\begin{aligned} d^*_{it} &= \pi' \mathbf{Z}_{it} + v_{it}, \\ d_{it} &= \begin{cases} 1 & if\ d^*_{it} \geq 0 \\ 0 & if\ d^*_{it} < 0. \end{cases} \end{aligned} \tag{11}$$

where $E(v_{it}) = 0. Var(v_{it}) = \sigma_v^2$ and $\mathbf{Z}_{it}$ is a vector of explanatory variables which includes determinants of the cost function.[9] This model accounts for differences when a firm exits. Applying standard econometric methods such as NSURE on the cost model will generally result in biased estimates and standard errors if v_{it} is correlated with u_{it} or ω_{mit} $(m = 1, \ldots. M - 1)$. This can be shown by taking the expected values of $ln(C_{it})$ and S_{mit} $(m = 1, \ldots, M - 1)$. Define $\mathbf{G}'_{it} = (ln(C_{it}), S_{1it}, \ldots, S_{M-1it})$, $\mathbf{H}'_{it} = (lnC(\ y_{it}. \mathbf{w}_{it}, \mathbf{q}_{it}, A_t), S_1(y_{it}, \mathbf{w}_{it}, \mathbf{q}_{it}. A_t). \ldots$

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[9] In our application $\mathbf{Z}_{it} = (y_{it}, \mathbf{w}_{it}, \mathbf{q}_{it})$.

$S_{M-1}(y_{it}, \mathbf{w}_{it}, \mathbf{q}_{it}, A_t))$ and $\mathbf{e}'_{it} = (u_{it}, \omega_{1it}, ..., \omega_{M-1it})$. We then have

$$\begin{aligned} E(\mathbf{G}_{it}) &= E(\mathbf{H}_{it} + \mathbf{e}_{it} \mid d_{it} = 1)\, p(d_{it} = 1) + E(\mathbf{H}_{it} + \mathbf{e}_{it} \mid d_{it} = 0)(1 - p(d_{it} = 1)) \\ &= \mathbf{H}_{it} + \left(E(\mathbf{e}_{it} \mid v_{it} \geq -\pi'\mathbf{Z}_{it}) - E(\mathbf{e}_{it} \mid v_{it} < -\pi'\mathbf{Z}_{it})\right) p(v_{it} \geq -\pi'\mathbf{Z}_{it}) \\ &+ E(\mathbf{e}_{it} \mid v_{it} < -\pi'\mathbf{Z}_{it}). \end{aligned} \tag{12}$$

Hence, we see from (12) that, in general, if $E(\mathbf{e}_{it} \mid v_{it} \geq -\pi'\mathbf{Z}_{it}) \neq E(\mathbf{e}_{it} \mid v_{it} < \pi'\mathbf{Z}_{it}) \neq 0$, that is, if $\mathbf{e}_{it}$ and v_{it} are correlated, the expected values of the error terms of the cost model are function of $\mathbf{Z}_{it}$ and, thus, of the determinants of the costs. On the other hand, if $\mathbf{e}_{it}$ and v_{it} are not correlated, exit may be considered as random and the model could be estimated by standard methods.

A common practice to avoid the problem of exit is to eliminate firms with incomplete time-series (sub-balancing). The estimation is therefore limited to the firms which never exit the sample. In that case, we obtain:

$$\begin{aligned} E(\mathbf{G}_{it} \mid d_{it} = 0) &= E(\mathbf{H}_{it} + \mathbf{e}_{it} \mid d_{it} = 0) \\ &= \mathbf{H}_{it} + E(\mathbf{e}_{it} \mid v_{it} < -\pi'\mathbf{Z}_{it}), \end{aligned} \tag{13}$$

and the estimation of the cost model on the subset of firms which never leave the sample will be biased if $E(\mathbf{e}_{it} \mid v_{it} < -\pi'\mathbf{Z}_{it}) \neq 0$, that is, again, if $\mathbf{e}_{it}$ and v_{it} are correlated.

The conclusion of the above discussion is that exit cannot be ignored in general and cannot be avoided by sub-balancing. The cost model must be estimated jointly with the exit model in order to obtain consistent parameters and standard errors.

Unlike exit, it is reasonable in the context of a cost model to consider entry as exogenous. However, it is likely that entering firms are different from those already in the sample. For that reason, a dummy variable for entry is included in the specification of the cost function. If this dummy variable has no significant effect on costs, entering firms are not different from those already in the sample. In most panel data sets of firms, entry occurs mainly because new firms are created or because firms are not surveyed in all periods. Both reasons could be viewed as exogenous and, therefore, not correlated to determinants of costs.

With a panel data set of firms, it is common to assume the existence of time invariant firm-specific effects[10]. In the context of a cost model, firm-specific effects are determinants of costs unobserved by the analyst but possibly observed by the firm's manager and not related to time. Firm-specific effects are associated with several factors, such as managerial efficiency (or inefficiency), experience, specific geographical conditions, etc. These effects may be correlated with the observed determinants of the costs (output, input prices, etc.).

In addition to firm-specific effects, time-specific effects must also be considered. The cost model described in the preceding section contains time effects (A_t) which influence the level of total costs and the slopes of the cost function with respect to its determinants. Time-specific effects must also be included in the exit model.

Should firm and time effects be considered as fixed or random? There are no formal rules to guide us in this choice. As stated by Hsiao, Lightwood and Hong Sun (1994): "One suggestion [...] is to assume at the outset that the effects are random" (p. 13). This statement relies on the view that, with fixed effects, inference is made conditional on the effects found in the sample, while with random effects inference is made with respect to the population of effects (Hsiao (1986), p. 42). In practice, the analyst does not always have the choice between fixed and random effects. The type of sample used often dictates the choice. For most panel data sets of firms, N (the number of firms) is quite large, while T (the number of periods) is usually relatively small. These characteristics favor the use of random effects for firm-specific effects and fixed effects for time. Moreover, the estimation of fixed time effects makes it easier to compute technical change since, in our cost model, time effects are associated with technical

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[10] See Hsiao (1986) for a complete treatment of panel data and, particularly, of specific effects.

change. In the case of firm-specific effects, since N may be quite large, the estimation of fixed effects may be costly in terms of degrees of freedom. Also, if the panel is short (T small), those fixed effects cannot be consistently estimated. In such panels, random firm-specific effects are therefore more appropriate.

Our econometric model considers firm-specific effects as random and time effects as fixed primarily because most of the panels used for the estimation of cost models contain a large number of firms but only a small number of time periods. Furthermore, fixed time effects are consistent with the specification of the cost function proposed by Baltagi and Griffin (1988). Our random firm effects are not correlated with other observed determinants of the costs. Some authors have suggested methods (see, for instance, Mundlak (1978)) which take into account the potential correlation between the firm-specific effects when considered as random and the other determinants of the model. However, these methods are quite ad hoc and it is beyond the scope of this paper to develop a robust method for that purpose.

Treating time effects as fixed and firm effects as random, the cost function may be written as:

$$\ell n(C_{it}) = \ell n C(y_{it}, \mathbf{w}_{it}, \mathbf{q}_{it}, A_t) + \theta_i + u_{it}, \tag{14}$$

where θ_i is a random firm-specific effect uncorrelated with the determinants of the cost with $E(\theta_i) = 0$ and $Var\ (\theta_i) = \sigma^2_\theta$.

Similarly, the exit model is:

$$\begin{aligned} d^*_{it} &= \pi'\mathbf{Z}_{it} + \lambda_t + \gamma_i + v_{it} \\ d_{it} &= \begin{cases} 1 & if\ d^*_{it} \geq 0 \\ 0 & if\ d^*_{it} < 0 \end{cases} \end{aligned} \tag{15}$$

where λ_t is a time-specific effect (fixed) and γ_i is a random firm-specific effect with $E(\gamma_i) = 0$ and $Var\ (\gamma_i) = \sigma^2_\gamma$.

The model defined by equations (14) and (15), along with the input share equations (10.2), is estimated under the following distributional assumptions:[11]

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[11] Assuming $M = 4$ as in our application.

$$(\gamma_i, \theta_i, v_{it}, u_{it}, \omega_{1it}, \ldots, \omega_{3it}) \sim N(0, \Omega),$$

where

$$\Omega = \begin{bmatrix} \sigma_\gamma^2 & \sigma_{\gamma\theta} & 0 & 0 & 0 & 0 & 0 \\ & \sigma_\theta^2 & 0 & 0 & 0 & 0 & 0 \\ & & \sigma_v^2 & \sigma_{vu} & \sigma_{v\omega_1} & \sigma_{v\omega_2} & \sigma_{v\omega_3} \\ & & & \sigma_u^2 & \sigma_{u\omega_1} & \sigma_{u\omega_2} & \sigma_{u\omega_3} \\ & & & & \sigma_{\omega_1}^2 & \sigma_{\omega_1\omega_2} & \sigma_{\omega_1\omega_3} \\ & & & & & \sigma_{\omega_2}^2 & \sigma_{\omega_2\omega_3} \\ & & & & & & \sigma_{\omega_3}^2 \end{bmatrix}$$

is the variance-covariance matrix. We also suppose that serial correlation comes from the firm-specific effects so that u_{it}, ω_{mit} and v_{it} are white-noise errors. This last assumption, along with the assumption that Ω is time invariant and that (γ_i, θ_i) is independent of the determinants of the costs, makes the estimation by maximum likelihood tractable. The likelihood function is presented in Appendix 1.

Before turning to the estimation and results, it is worth noting that the above model considers the correlation that might exist between θ_i and γ_i. For instance, if θ_i is associated with managerial efficiency and γ_i with some kind of propensity to exit, the two effects may be correlated. Also, this association between γ_i and the propensity of a firm to exit (regardless of the time period) allows for differences between exiting and non-exiting firms not only when the former are about to exit, but for all periods.

4. An Application to the Ontario Trucking Industry

4.1 Data and Variables

Our data set consists of 445 yearly observations of general freight carriers in Ontario between 1981 and 1988. It includes 163 different firms for which information is available for 2.7 years on average. This data set has been created from a census and a survey which were both conducted by Statistics Canada: the Motor Carrier Freight (MCF) census and the Origin-Destination Trucking (TOD) survey. The MCF census contains information on inputs and costs for all trucking firms with annual revenues in excess of $1,000,000. It includes the financial statements as well as data on unemployment, fuel consumption, equipment, etc. The TOD survey contains a sample of shipments carried by a subset of the firms in the MCF census. For each shipment surveyed, information on the origin, the destination, the type of commodity, the weight, and the revenues generated by the shipment are available.

In this panel data set, several time series of firms are incomplete for numerous possible reasons: 1) a firm may not be surveyed each year by the TOD survey; 2) for unknown reasons, a firm may decide not to answer the MCF census or the TOD survey or both; 3) a firm may go out of business or be involved in a merger or an acquisition; and 4) a firm may enter into the industry after the first period, which is treated as an exogenous phenomenon. Since we only observe that a firm was exiting the sample and not the reason why, no distinction is possible among the different types of exit. Thus, exit is treated as endogenous regardless of the reason it occurs.

Movements of entry and exit in our sample are very important. For instance, any attempt to estimate a cost function with a sub-balanced panel would be impossible, since only 7 firms have complete time series. Also, let us recall that to get consistent estimates of A_t (the index of technical change), the number of firms at each period must be sufficiently large.

The identification of exiting firms is not possible for 1988 since we do not have any reliable information on trucking firms in 1989.[12] Therefore, the econometric analysis is limited to the years 1981 to 1987 and the 1988 data are used to identify exiting firms in 1987. Among the 146 different firms in the 1981–1987 panel, 61 appear in only one period. This high proportion of single-appearance firms makes it difficult to estimate the parameters ϕ_y, ψ_m and μ_u because they are not identifiable for these firms. Therefore, the analysis is limited to firms which appear in the panel in at least two time periods (not necessarily consecutively). The reduced sample contains

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[12] In 1989, Statistics Canada changed its survey methods, and now both the MCF and the TOD are surveys. Furthermore, for budgetary reasons, sample survey sizes have been reduced.

322 observations on 85 different trucking firms. Firms are in the sample for 3.8 years on average.

The specific definitions of the variables included in the econometric model are given as follows:

C : total operating costs, including a 10% opportunity cost of capital ($);

w_1 : price of fuel, including taxes ($/litre);

w_2 : price of labor, including fringe benefits ($/person-year);

w_3 : price of capital, including opportunity cost ($/$ value of capital stock);

w_4 : price of materials, a Divisia index of the prices of all other inputs ($);

y : total number of shipments;

q_1 : average length of the haul (kilometers);

q_2 : average shipment size (tons);

q_3 : average load per truck (ton/vehicle-kilometer);

q_4 : insurance for loss and damage ($/ton-kilometer).

In addition, the following dummy variables are used:

$d_{it} = 1$, if firm i is exiting the sample at period $t: d_{it} = 0$ otherwise;

$de_{it} = 1$, if firm i is entering the sample at period $t; de_{it} = 0$ otherwise;

$dt_{it} = 1$ at period $t; dt_{it} = 0$ otherwise.

Table 1 presents the mean of these variables.

(Table 1 about here)

While the inclusion of the output[13] (y) and input price (w) variables in the specification of a cost function is usual, the presence of technological characteristics (q) is less common. These variables are included to reflect two particular aspects of the technology of trucking firms. These firms produce a heterogenous output and operate over a network with specific attributes.

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[13] We measure the level of output with the number of shipments instead of the usual ton-miles since it permits to obtain directly the cost elasticities with respect to technological characteristics. Both measures are equivalent for estimation purpose with the translog specification (Gagné, 1990).

Heterogeneity of the output is taken into account with the average length of the haul (q_1), the average shipment size (q_2) and the insurance expenses for loss and damage (q_4). This last variable is included to reflect the different mix of goods a firm may carry. Higher expenses for insurance are a proxy for a mix which includes more fragile goods or goods which need particular care. The average length of the haul and shipment size reflect differences among shipments in terms of distance and weight. The average length of the haul may also be considered as a network attribute reflecting its size. The average load per truck (q_3) is a network variable which controls mainly for the level of empty returns.[14]

4.2 Estimation Results

a) General Results

In Table 2, we present the results of maximum likelihood estimation. Two types of specifications are considered: no firm-specific effects and random firm-specific effects. In column 1, results were obtained from the non-joint estimation of the cost model and the exit equation; i.e., under the constraint that the covariances between $(u, \omega_1, \omega_2, \omega_3)$ and ν are equal to zero (model 1). Column 2 shows the equivalent results with the constraint on the covariances relaxed (model 2). Columns 3 and 4 show the estimates obtained from models similar to those of column 1 and 2, except that in these cases random firm-specific effects are included in the cost and exit equations (models 3 and 4). Note that since each firm is in the panel for at least 2 years, exit is not possible in 1981. Therefore, d82 is excluded from the exit equation in order to identify its intercept parameter.

(Table 2 about here)

Using a likelihood ratio (LR) test as a mean of comparison between the models, it is clear that the specifications which include firm effects dominate.[15] Not only does the log-likelihood

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[14] The reader is referred to the seminal paper of Spady and Friedlaender (1978) and also to their book (Spady and Friedlaender, 1981) for a complete discussion on output and network attributes in cost functions.

[15] The LR test statistics are 60.93 for model 3 vs. model 1 and 62.10 for model 4 vs. model 2. In both cases, it is greater than a χ^2 at the 1 percent confidence level with 2 or 3 degrees of freedom.

rise significantly with the addition of random firm effects, but some parameter estimates are also considerably affected, notably, parameters associated with time and, therefore, with technical change.

For instance, the estimated indexes of technical change (A) are 25% lower on average with the random effect specifications (Table 2). A closer look at the variance-covariance matrix parameters reveals that these gains on the log-likelihood come almost exclusively from the introduction of random firm effects in the cost function. In fact, only the estimated variance of θ (the random effect of the cost function) is significant in models 3 and 4. No firm-specific effect appears to be relevant in the exit equation.

In order to judge the relevance of estimating the cost model and the exit equation jointly, we also compared model 2 to model 1 and model 4 to model 3 using LR tests. In the case of models 1 and 2, the LR test statistic is 8.63, which is greater than a χ^2 with 4 degrees of freedom at the 10 percent confidence level (7.78). The LR test statistic between models 3 and 4 is 9.80, which is also greater than a χ^2 with 5 degrees of freedom at the 10 percent confidence level (9.24). On the basis of this test alone, it seems that the non-joint estimation has to be marginally rejected. This weak rejection of the non-joint estimation is confirmed by the results on the covariance estimates between u, ω, θ and v, γ. Among the 5 possible covariances which are introduced in the joint specification, one ($\sigma_{v\omega_3}$) is statistically different from zero in models 2 and 4. In both cases, the correlation is negative, indicating a higher probability of exit for firms having a smaller capital share (ceteris paribus).

The marginal rejection of the non-joint specification seems to indicate that in this panel data set, exit cannot be considered as exogenous if a 10 percent confidence level is sufficiently convincing. However, this result obscures an important fact: none of the parameters in the exit equation, with the exception of $\pi_{11}(d84), \pi_{12}(d85), \pi_{13}(d86), \pi_{14}(d87)$, is statistically significant. Therefore, even if we find a significant correlation between some random variables, it is not clear that the estimation of the cost model alone will lead to biased parameter estimates since there are no correlations between the error terms and the determinants of the model. However, it remains that the small superiority of the joint model (cost and exit) indicates the presence of an exit bias. In that case, standard errors are biased if the distribution of the error term is misspecified. In fact, there is a slight difference between the asymptotic t-ratios computed in models 3 and 4, although these differences do not change the conclusions on the statistical significance of the estimated parameters. On the other hand, exit seems to be closely related to time, which is a crucial determinant in our cost model for the inference of technical change. Consequently, the joint estimation of the cost model and the exit equation is preferred to the non-joint estimation.

The significant time parameters in the exit equation are all positive, indicating a higher probability of exit after 1983. In 1984, announcements were made by the regulating authorities concerning the removal of economic regulations in the transportation industries in Canada. These announcements were followed by a weaker application of existing regulations as well as by a gradual elimination of these regulations. By 1988, the trucking industry was no longer ruled by governmental economic regulations (at least for domestic operations). The higher probability of exit after 1983 estimated by our model seems to be related to the anticipation of regulatory changes by the trucking firms. This relation between deregulation and time offers another argument in favor of the estimation of the joint model, since in that case the joint estimation is more likely to provide unbiased estimates of the indexes of technical change. Otherwise, the indexes of technical change obtained from the estimation of the cost model alone may contain a mixture of pure technical change and deregulation effects. In fact, when comparing the indexes of technical change of models 3 and 4, we see that those of model 4 are systematically (although marginally) higher than those of model 3. Also, A86 is statistically significant in model 4 while it is not in model 3. Results on technical change are discussed in greater detail in the next section. Finally, in all models considered, the entry parameter (α) is never statistically significant. Therefore, entering firms are not different from the others already in the panel.

Our results on selectivity are similar to those of Hausman and Wise (1978), obtained with different model and data. Their conclusion is that the selection bias they found was diminishing and even disappearing with the improvement of the specification of the outcome equation. Here, we have a very fine specification of the cost function because we have very good data. In most cases, technological characteristics are not available; only output and input prices are used to estimate the cost function.[16] In such circumstances, the quality of the specification of the outcome equation is less efficient to control for the potential exit bias. This point is illustrated by the results presented in Table 3 where we have voluntarily used a less good specification of the cost and exit models by removing all the technological characteristics. Model 5 is the non-joint estimation of the cost model and exit equation and model 6 is the joint estimation. The results show a clear domination of the joint estimation. The LR test statistic between the two models is 16.97, which is greater than a χ^2 with 5 degrees of freedom at the 1 percent confidence level (15.1). In addition, a term of covariance between the two models ($\sigma_{v\omega_1}$) is statistically significant. Some parameters (notably b_y) and standard errors are affected by the joint estimation and several time variables in the exit equation are statistically significant. This results emphasize the relationship between specification and selection bias. With the diminution of the quality of the specification, the selection bias becomes more apparent.

(Table 3 about here)

b) Technological Measurements

Table 4 summarizes the technological measurements computed from the estimated parameters of models 1 to 4. All computations were made at the sample means. These measures are local and second-order parameters of the translog approximation of the cost function are not needed

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[16] See, for instance, Baltagi and Griffin (1988) on the estimation of a cost function for electric utilities.

except for the elasticities of substitution (c_{ms}). In Table 5 we present the second-order parameters used for the computation of the elasticities of substitution.

(Table 4 about here)

The first line of Table 4 gives the measure of returns to scale. For all estimated models, returns to scale are increasing for the average firm in the sample. However, random specifications, which are preferred, give a higher level of increasing returns to scale. In Table 5, we also present the estimates of the second-order parameters corresponding to $\tilde{y}^2\,(b_{yy})$. When $b_{yy} > 0$, the average cost function is U-shaped. This parameter is positive for all models, but is significant only in the non-random specifications.

(Table 5 about here)

We thus conclude that the average firm in this sample is operating at increasing returns to scale and, therefore, has not yet exhausted all its returns to scale. This conclusion is the same whether we use model 3 or 4. Hence, the joint estimation of the cost model and the exit equation does not affect conclusions on returns to scale with our panel data set.

Regardless of the specification, estimates always show a declining rate of technical change over the period considered. The decline is, however, less pronounced with the joint specification (model 4). The results show an erratic pattern of evolution, confirming the importance of using a dummy variable specification and a panel data set for the estimation of technical change. Estimates of technical change show less volatility with the random specifications (models 3 and 4), although estimates obtained with the joint specification seem to be slightly more volatile than those obtained with the non-joint specification. Again here, the results are not significantly affected by the joint estimation of the cost model and the exit equation.

Estimates of the elasticities of substitution are affected mainly when random firm-specific effects are introduced into the cost function. For instance, model 2 indicates a complementarity relationship between fuel and labor. This relationship turns out to be more substitute with the random specifications and no significant differences are observed between the joint and the non-joint specifications.

As far as technological measurements are concerned, it seems that the joint estimation of the cost model and the exit equation did not significantly alter the results. On the other hand, the inclusion of random firm-specific effects did slightly change some technological measurements. Of course, these results are conditional on the sample used.

5. Conclusion

We developed a methodology for the estimation of a cost model with incomplete panel data. This methodology considers entry into the panel after the first period under study as exogenous but exit before the last period as endogenous. Thus, an exit model is jointly estimated with the cost model. Both cost and exit models include random firm-specific effects. The cost function is approximated by a translog form. However, other approximations may be considered with this methodology.

Our methodology detects and corrects the bias which occurs if the random variables of the cost model (residuals and random effects) are correlated with those of the exit model. As an illustrative example, we applied the methodology to an incomplete panel of trucking firms in Ontario. Empirical results show some evidence of correlation between the random variables of the cost and those of the exit equation. Furthermore, we established that the selection bias is related to the specification of the cost function. A better specification seems to reduce the importance of the bias in terms of parameter estimates and standard errors. Hence, even if our method does not correct for specification errors, this result indicates that it has to be used to correct for selectivity when appropriate data are not available to improve the specification, which is often the case in many applications. Finally, technological parameters computed from the estimates of the joint model (cost and exit) are not significantly different from those obtained with the estimation of the cost model alone. Hence, even if a selection bias was found in our sample, it does not seem to affect the technological measurements. Of course, the results are specific to the data used and should be interpreted as such.

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Appendix 1: Likelihood Function and Estimation Procedure

Assuming that $(\gamma_i, \theta_i, v_{it}, u_{it}, \omega_{1it}, \omega_{2it}, \omega_{3it}) \sim N(0, \Omega)$,

where

$$\Omega = \begin{bmatrix} \sigma_\gamma^2 & \sigma_{\gamma\theta} & 0 & 0 & 0 & 0 & 0 \\ & \sigma_\theta^2 & 0 & 0 & 0 & 0 & 0 \\ & & \sigma_v^2 & \sigma_{vu} & \sigma_{v\omega_1} & \sigma_{v\omega_2} & \sigma_{v\omega_3} \\ & & & \sigma_u^2 & \sigma_{u\omega_1} & \sigma_{u\omega_2} & \sigma_{u\omega_3} \\ & & & & \sigma_{\omega_1}^2 & \sigma_{\omega_1\omega_2} & \sigma_{\omega_1\omega_3} \\ & & & & & \sigma_{\omega_2}^2 & \sigma_{\omega_2\omega_3} \\ & & & & & & \sigma_{\omega_3}^2 \end{bmatrix} = \begin{bmatrix} \sum_{\gamma\theta} & 0 \\ 0 & \sum_{vu\omega} \end{bmatrix};$$

the joint distribution of

$$(\gamma_i + v_{i1}, \theta_i + u_{i1}, \omega_{1i1}, \omega_{2i1}, \omega_{3i1}, \ldots, \gamma_i + v_{iT_i}, \theta_i + u_{iT_i}, \omega_{1iT_i}, \omega_{2iT_i}, \omega_{3iT_i})$$

is $N(0, \sum^*)$ where

$$\sum{}^* = \left[ii' \otimes \begin{bmatrix} \sum_{\gamma\theta} & 0_{2\times 3} \\ 0_{3\times 2} & 0_{3\times 3} \end{bmatrix} + \mathrm{I}_{T_i} \otimes \sum_{vu\omega} \right],$$

i is a $(T_i \times 1)$ vector of ones and $\otimes$ denotes the Kronecker product operator.

The likelihood of the i firm in the sample is given by the following T_i-fold integral:

$$L_i = \int_{-\infty}^{a_{iT_i}} \cdots \int_{-\infty}^{a_{i1}} f(\gamma_i + v_{i1}, \theta_i + u_{i1}, \omega_{1i1}, \ldots, \omega_{3iT_i}) d(\gamma_i + v_{i1}) \ldots d(\gamma_i + v_{iT_i}), \qquad \text{(A1)}$$

where $a_{it} = (\pi' Z_{it} + \lambda_t)(2d_{it} - 1)$. In our application, T_i can be equal to 7. This makes the integral in (A1) computationally intractable. However, the imposed covariance structure allows us to use a factorization similar to Keane, Moffit and Runkle (1988) by conditioning on γ_i and θ_i. It is then possible to reduce the order of integration to two. Therefore, (A1) becomes

$$L_i = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left(\prod_{T_i} P_{it} \right) \cdot f_1(\gamma_i, \theta_i)\, d\theta_i\, d\gamma_i. \qquad \text{(A2)}$$

where $P_{it} = \int_{-\infty}^{a_{it}} f_2(\gamma_1 + v_{it}, \theta_i + u_{it}, \omega_{1it}, \omega_{2it}, \omega_{3it} \mid \gamma_i, \theta_i) d(v_{it})$, f_1 is a bivariate normal density with mean zero and covariance matrix $\sum_{\gamma\theta}$ and f_2 is a five-dimension normal distribution with mean $[\gamma_i\ \theta_i\ 0\ 0\ 0]$ and covariance matrix $\sum_{vu\omega}$. Equivalently, f_2 may be written as

$$f(\theta_i + u_{it}, \omega_{1it}, \omega_{2it}, \omega_{3it} \mid \gamma_i, \theta_i) f(\gamma_i + v_{it} \mid \theta_i + u_{it}, \omega_{1it}, \omega_{2it}, \omega_{3it}, \gamma_i, \theta_i).$$

Define $\sum_{u\omega}$ as the (4x4) submatrix located at the lower right corner of $\sum_{vu\omega}$ and $C_{v,u\omega}$ as the (1x4) vector located at the upper right corner of $\sum_{vu\omega}$. Then, $f(\theta_i + u_{it}, \omega_{1it}, \omega_{2it}, \omega_{3it} \mid \gamma_i, \theta_i)$ is a four-dimension normal distribution with mean $[\theta_i 000]$ and covariance matrix $\sum_{uw}$; $f(\gamma_i + v_{it} \mid \theta_i + u_{it}, \omega_{1it}, \omega_{2it}, \omega_{3it}, \gamma_i, \theta_i)$ is the univariate normal distribution with mean $\left(\gamma_i + C_{v,u\omega} \sum_{u\omega}^{-1} [u_{it}\, \omega_{1it}\, \omega_{2it}\, \omega_{3it}]'\right)$ and variance $\left(\sigma_v^2 - C_{v,u\omega} \sum_{u\omega}^{-1} C'_{v,u\omega}\right)$. P_{it} in (A2) may now be written as:

$$N\left([\theta_i 000], \sum_{u\omega}\right) \int_{-\infty}^{a_i T} N\left(\left(\gamma_i + C_{v,u\omega} \sum_{uw}^{-1} [u_{it}\, \omega_{1it}\, \omega_{2it}\, \omega_{3it}]'\right),\right. \qquad \text{(A3)}$$

$$\left.\left(\sigma_v^2 - C_{vu\omega} \sum_{u\omega}^{-1} C'_{v,u\omega}\right)\right) d(v_{it}).$$

Substituting (A3) in (A2) leads to

$$L_i = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \prod_{T_i} \left\{ N([\theta_i 000], \Sigma_{u\omega}) \int_{-\infty}^{a_{it}} N\left(\gamma_i + C_{v,u\omega} \Sigma_{u\omega}^{-1} (u_{1t}\, \omega_{1it}\, \omega_{2it}\, \omega_{3it})'.\right.\right. \qquad \text{(A4)}$$

$$\left.\left.\left(\sigma_v^2 - C_{v,u\omega} \Sigma_{u\omega}^{-1}\, C'_{v,u\omega}\right)\right) d(v_{it}) \right\}. N(0, \Sigma_{\gamma\theta}) d\theta_i d\gamma_i$$

For identification purposes (d_{it} is a binary dependent variable) and computational ease, we used equivalent but slightly different expressions for equations (14) and (15) in the text:

$$\ell n(C_{it}) = \ell n\, C(y_{it}, w_{it}, q_{it}. A_t) + \sigma_\theta \overline{\theta}_i + u_{it} \qquad \text{(A5)}$$

and

$$d^*_{it} = \pi' Z_{it} + \lambda_t + \sigma_\gamma \overline{\gamma}_i + v_{it} \qquad \text{(A6)}$$

where $f(\overline{\gamma}_i, \overline{\theta}_i) = N(0, R)$ and $R = \begin{bmatrix} 1 & \rho_{\gamma\theta} \\ & 1 \end{bmatrix}$. We also imposed that $\sigma_v^2 = 1$.

It follows that

$$f(\overline{\gamma}_i, \overline{\theta}_i, v_{it}, u_{it}, \omega_{1it}, \omega_{2it}, \omega_{3it}) \sim N(0, \overline{\Omega}) \qquad \text{(A7)}$$

where

$$\overline{\Omega} = \begin{bmatrix} 1 & \rho_{\gamma\theta} & 0 & 0 & 0 & 0 & 0 \\ & 1 & 0 & 0 & 0 & 0 & 0 \\ & & 1 & \overline{\sigma}_{vu} & \overline{\sigma}_{v\omega_1} & \overline{\sigma}_{v\omega_2} & \overline{\sigma}_{v\omega_3} \\ & & & \sigma_u^2 & \sigma_{u\omega_1} & \sigma_{u\omega_2} & \sigma_{u\omega_3} \\ & & & & \sigma_{\omega_1}^2 & \sigma_{\omega_1\omega_2} & \sigma_{\omega_1\omega_3} \\ & & & & & \sigma_{\omega_2}^2 & \sigma_{\omega_2\omega_3} \\ & & & & & & \sigma_{\omega_3}^2 \end{bmatrix} = \begin{bmatrix} R_{\gamma\theta} & 0 \\ 0 & \overline{\Sigma}_{vu\omega} \end{bmatrix}$$

and $\overline{\Sigma}_{vu\omega} = \begin{bmatrix} 1 & \overline{C}_{v,u,\omega} \\ \overline{C}'_{v,u\omega} & \Sigma_{u\omega} \end{bmatrix}$.

Substituting (A7) in (A2) leads to

$$L_i = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \prod_{T_i} \left\{ N\left[(\sigma_\theta \overline{\theta}_i\, 000), \Sigma_{u\omega}\right] \Phi \left[\frac{\left(\pi' Z_{it} + \lambda_t - \sigma_\gamma \overline{\gamma}_i - \overline{C}_{v,u\omega}\, \Sigma_{u\omega}^{-1} \left(u_{it}\, \omega_{1it}\, \omega_{2it}\, \omega_{3it}\right)'\right)(2d_{it} - 1)}{\sqrt{1 - \overline{C}_{v,u\omega}\, \Sigma_{u\omega}^{-1}\, \overline{C}'_{v,u\omega}}} \right]. \right.$$

$$\cdot N(0, R_{\gamma\theta})\, d\overline{\theta}_i\, d\overline{\gamma}_i, \tag{A8}$$

where $\Phi(\cdot\cdot)$ is the standard normal CDF evaluated at $(\cdot\cdot)$.

The double integral in (A8) can be numerically evaluated by using the Gaussian quadrature method of the form: $\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g(x, y)dxdy = \sum_{j=1}^{n} w_j \sum_{i=1}^{n} w_i g(x_i, y_j)$ where the w's and x's are quadrature weights and points from nth degrees Hermite polynomial (see Abramowitz and Stegun (1965)).

Butler and Moffit (1982) obtained satisfactory accuracy by using 4–5 quadrature points for univariate integration in a panel-probit model. Keane, Moffit and Runkle (1988) evaluated some two-fold integrals by quadrature technique without reporting the number of quadrature points used. The results presented in this paper were obtained by using 20 quadrature points, that is 20^2 function evaluations per integral evaluation. However, experience showed that going from 12 to 16 or even 20 points did not affect the log-likelihood of the sample by more than 10^{-7}. Moreover, estimated parameters obtained by using the 6 point quadrature technique proved to be comparable to the 20 point estimates: significant parameters are the same and the change in estimated coefficients is less than 15%.

All our maximum likelihood estimates were obtained by using the Broyden, Fletcher, Goldfarb and Shanno algorithm provided in the Maxlik module of the GAUSS 3.0 software and using analytical derivatives.

Table 1. Means of the Variables
(85 firms, 322 observations)

Variable	*Mean*
C (Total costs)	171 622.98
w_1 (Fuel)	0.38
w_2 (Labor)	30 366.22
w_3 (Capital)	0.92
w_4 (Materials)	7 561.04
q_1 (Length of haul)	547.91
q_2 (Shipment size)	7.76
q_3 (Load per truck)	0.07
q_4 (Insurance)	0.01
S_1 (Fuel share)	0.09
S_2 (Labor share)	0.22
S_3 (Capital share)	0.24
S_4 (Material share)	0.45
d (Exit)	0.1460
de (Entry)	0.1366
d81	0.1273
d82	0.1460
d83	0.1460
d84	0.1460
d85	0.1491
d86	0.1522
d87	0.1335

Table 2. Parameter Estimates by Maximum Likelihood[1]
(Asymptotic t-Ratios)

		No Firm-Specific Effects		*Random Firm-Specific Effects*	
Parameter	Variable	(1)	(2)	(3)	(4)
Cost Function					
a_o	Intercept	18.3465* (60.3428)	18.1886* (61.2366)	18.2898* (66.6481)	18.2744* (67.1683)
b_y	$\tilde{y}$	0.8504* (13.7789)	0.8502* (14.0454)	0.8231* (12.1196)	0.8283* (12.2107)
c_1	$\tilde{w}_1$	0.0212** (2.0307)	0.0232** (2.2309)	0.0210** (2.0049)	0.0198*** (1.8836)
c_2	$\tilde{w}_2$	0.1286* (7.6666)	0.1305* (7.8492)	0.1310* (7.8582)	0.1304* (7.6741)
c_3	$\tilde{w}_3$	0.1800* (13.2103)	0.1828* (13.8171)	0.1789* (13.2187)	0.1789* (13.1727)
d_1	$\tilde{q}_1$	0.6004* (6.4986)	0.5929* (6.5346)	0.6005* (5.8128)	0.6049* (5.3601)
d_2	$\tilde{q}_2$	0.7036* (7.3735)	0.7040* (7.4573)	0.6956* (7.1717)	0.7011* (7.3123)
d_3	$\tilde{q}_3$	-0.1679*** (-1.7900)	-0.1746*** (-1.9094)	-0.1402*** (-1.6876)	-0.1508*** (-1.8154)
d_4	$\tilde{q}_4$	0.1756** (2.1785)	0.1706** (2.1330)	0.2172* (2.9215)	0.2068* (2.7724)
ϕ_y	$dt * \tilde{y}$	0.2028* (2.7539)	0.2068* (2.7152)	0.2847** (2.3778)	0.2645** (2.3913)
ψ_1	$dt * \tilde{w}_1$	0.0063 (0.5008)	0.0063 (0.4497)	0.0135 (0.6611)	0.0136 (0.6832)
ψ_2	$dt * \tilde{w}_2$	0.0129 (0.5536)	0.0132 (0.5390)	0.0225 (0.6710)	0.0220 (0.6892)
ψ_3	$dt * \tilde{w}_3$	-0.0011 (-0.0689)	-0.0010 (-0.0619)	0.0085 (0.3880)	0.0094 (0.4433)

Table 2. (Continued) Parameter Estimates by Maximum Likelihood[1] (Asymptotic t-Ratios)

Parameter	Variable	*No Firm-Specific Effects*		*Random Firm-Specific Effects*	
		(1)	(2)	(3)	(4)
μ_1	$dt * \tilde{q}_1$	0.1122*** (1.1726)	0.1131 (1.1264)	0.0387 (0.3397)	0.021 (0.131
μ_2	$dt * \tilde{q}_2$	0.2680* (3.7021)	0.2739* (3.6276)	0.3659* (2.9811)	0.341 (3.027
μ_3	$dt * \tilde{q}_3$	0.1691** (2.1977)	0.1773** (2.1867)	0.1026 (1.1427)	0.1164 (1.2613
μ_4	$dt * \tilde{q}_4$	0.1433* (4.1053)	0.1490* (4.0323)	0.1280* (2.7158)	0.1331 (2.9429
A82	d82	0.0777 (0.4341)	0.0774 (0.4524)	0.0783 (0.6697)	0.0960 (0.8072
A83	d83	0.4820** (2.4639)	0.4682** (2.4408)	0.3285** (1.9915)	0.3485 (2.0837)
A84	d84	0.4589** (2.0817)	0.4434** (2.0611)	0.2741 (1.5720)	0.2836 (1.6337)
A85	d85	0.5234* (2.6440)	0.5066* (2.6369)	0.3916** (2.2188)	0.4082* (2.2244)
A86	d86	0.5637** (2.1011)	0.5496** (2.1053)	0.4244 (1.8966)	0.4555* (2.0590)
A87	d87	0.5243** (2.4428)	0.5020** (2.4138)	0.3865** (2.0139)	0.3914* (2.0505)
α	de	-0.0274 (-0.6222)	-0.0317 (-0.7067)	-0.0064 (-.1758)	-0.0130 (-0.3164)
Exit Equation					
π_0	Intercept	-1.3536** (-2.4518)	-1.3506** (-2.1771)	-1.6315*** (-1.8406)	-1.6332** (-1.9058)
π_1	y	-0.0322 (-0.5060)	-0.0484 (-0.8012)	-0.0353 (-0.5819)	-0.0491 (-0.6610)
π_2	w_1	-0.0512 (-0.1592)	-0.0815 (-0.2462)	-0.0130 (-0.2790)	-0.0938 (-0.2789)
π_3	w_2	-0.7510***	-0.7703***	-0.8005	-0.8422

Table 2. (Continued) Parameter Estimates by Maximum Likelihood[1]
(Asymptotic t-Ratios)

Parameter	Variable	*No Firm-Specific Effects* (1)	(2)	*Random Firm-Specific Effects* (3)	(4)
		(-1.7363)	(-1.6836)	(-1.6129)	(-1.5459)
π_4	w_3	0.0353 (0.2522)	0.0545 (0.3685)	0.0580 (0.3151)	0.0674 (0.3027)
π_5	w_4	0.0720 (0.6544)	0.1618 (1.2829)	0.0714 (0.5689)	0.1761 (1.0354)
π_6	q_1	0.0839 (0.9582)	0.0837 (1.0073)	0.0970 (0.9630)	0.1157 (1.0586)
π_7	q_2	0.0447 (0.4668)	0.0319 (0.3340)	0.0275 (0.2214)	0.0330 (0.2324)
π_8	q_3	0.0831*** (1.8400)	0.0842*** (1.8815)	0.1003*** (1.6509)	0.0987*** (1.6493)
π_9	q_4	0.0562 (0.9782)	0.0344 (0.5620)	0.0622 (0.9451)	0.0464 (0.6670)
π_{10}	d83	-0.0450 (-0.1061)	-0.0740 (-0.1747)	0.0187 (0.0450)	0.0281 (0.0995)
π_{11}	d84	0.9829* (2.8707)	0.9120* (2.6695)	1.2334** (2.3245)	1.1445* (2.6543)
π_{12}	d85	1.1456* (3.4044)	1.1647* (3.5474)	1.3843* (2.6644)	1.4181* (3.2778)
π_{13}	d86	1.0929* (3.1003)	1.0620* (3.0075)	1.4003* (2.3015)	1.4535* (2.8158)
π_{14}	d87	1.2042* (3.4301)	1.1563* (3.3112)	1.6059* (2.1848)	1.5583* (2.5715)
Variance-Covariance Matrix Parameters					
σ_u^2		0.2364* (11.8594)	0.2365* (11.8380)	0.2134* (9.6515)	0.2122* (9.6188)
$\sigma_{\omega_1}^2$		0.0020* (11.0949)	0.0020* (11.0822)	0.0020* (11.1902)	0.0020* (11.2397)
$\sigma_{\omega_2}^2$		0.0050*	0.0050*	0.0050*	0.0051*

Table 2. (Continued) **Parameter Estimates by Maximum Likelihood[1]** **(Asymptotic t-Ratios)**

Parameter	Variable	*No Firm-Specific Effects* (1)	*No Firm-Specific Effects* (2)	*Random Firm-Specific Effects* (3)	*Random Firm-Specific Effects* (4)
		(11.3402)	(11.3178)	(10.9977)	(10.977
$\sigma^2_{\omega_3}$		0.0033* (12.6431)	0.0033* (12.6378)	0.0032* (12.6410)	0.003 (12.250
$\sigma_{u\omega_1}$		-0.0180* (-10.4012)	-0.0181* (-10.3931)	-0.0185* (-10.3864)	-0.018 (-16.473
$\sigma_{u\omega_2}$		-0.0220* (-8.4434)	-0.0221* (-8.4414)	-0.0214* (-7.2310)	-0.021 (-8.812
$\sigma_{u\omega_3}$		-0.0016 (-0.8736)	-0.0015 (-0.8227)	-0.0031 (-1.5810)	-0.0028 (-1.3983
$\sigma_{\omega_1\omega_2}$		0.0014* (6.7031)	0.0015* (6.7062)	0.0015* (6.5586)	0.0015 (6.4582
$\sigma_{\omega_1\omega_3}$		0.0002 (1.4602)	0.0002 (1.3940)	0.0003 (1.6214)	0.0002 (1.2088)
$\sigma_{\omega_2\omega_3}$		0.0002 (0.7855)	0.0002 (0.7383)	0.0002 (0.9330)	0.0003 (1.0570)
σ^2_θ		-	-	0.0351* (4.0462)	0.0355* (4.0099)
$\sigma_{\gamma\theta}/\sigma_\gamma\sigma_\theta$		-	-	-	-0.1841 (-0.6438)
σ_{vu}		-	-0.0399 (-0.7263)	-	-0.0283 (-0.3805)
$\sigma_{v\omega_1}$		-	0.0066 (1.4545)	-	0.0084 (1.2539)
$\sigma_{v\omega_2}$		-	0.0019 (0.2657)	-	-0.0014 (-0.1396)
$\sigma_{v\omega_3}$		-	-0.0110** (-2.0854)	-	-0.0133** (-2.0218)
σ_γ		-	-	0.5518 (1.1591)	0.5882 (1.4538)

Table 2. (Continued) Parameter Estimates by Maximum Likelihood[1]
(Asymptotic t-Ratios)

		No Firm-Specific Effects		*Random Firm-Specific Effects*	
Parameter	Variable	(1)	(2)	(3)	(4)
Log-likelihood		1349.5215	1353.8375	1379.9875	1384.8882
Nb. of estimated parameters		85	89	87	92
Nb. of observations		322	322	322	322

1- Only the first-order parameters of the translog are presented here. Complete results may be obtained from the authors upon request.

* Statistically significant at the 1 percent confidence level.
** Statistically significant at the 5 percent confidence level.
*** Statistically significant at the 10 percent confidence level.

Table 3. Parameter Estimates by Maximum Likelihood-No Technological Characteristics[1] (Asymptotic t-Ratios)

		Random Firm-Specific Effects	
Parameter	Variable	(5)	(6)
Cost Function			
a_o	Intercept	16.2133* (108.8384)	16.2280* (276.3977)
b_y	$\tilde{y}$	0.1612* (2.8968)	0.2727* (12.1058)
c_1	$\tilde{w}_1$	0.0854* (21.1576)	0.0852* (19.8772)
c_2	$\tilde{w}_2$	0.2302* (30.7036)	0.2309* 29.0058)
c_3	$\tilde{w}_3$	0.2190* (42.7749)	0.2202* (40.3258)
o_y	$dt * \tilde{y}$	0.0186 (0.2848)	-0.0015 (-0.0169)
v_1	$dt * \tilde{w}_1$	0.0081 (0.4378)	0.0049 (0.2262)
v_2	$dt * \tilde{w}_2$	0.0306 (0.9287)	0.0285 (0.7493)
v_3	$dt * \tilde{w}_3$	0.0012 (0.0507)	-0.0018 (-0.0684)
A82	d82	-0.0125 (-0.2133)	0.0210 (0.3260)
A83	d83	0.0407 (0.6460)	0.0523 (0.7881)
A84	d84	0.0520 (0.8064)	0.0636 (0.9648)
A85	d85	0.1962* (2.8397)	0.1830** (2.4741)

Table 3. (Continued) Parameter Estimates by Maximum Likelihood-No Technological Characteristics[1]
(Asymptotic t-Ratios)

		Random Firm-Specific Effects	
Parameter	Variable	(5)	(6)
A86	d86	0.3093* (4.5457)	0.3075* (4.2145)
A87	d87	0.3535* (4.6037)	0.3196* (4.2192)
α	de	-0.0924 (-1.6416)	-0.1042*** (-1.7876)
Exit Equation			
π_0	Intercept	-1.1656*** (-1.8463)	-1.0499 (-1.5686)
π_1	y	-0.0429 (-0.7989)	-0.0198 (-0.3357)
π_2	w_1	0.0765 (0.2131)	-0.0088 (-0.0241)
π_3	w_2	-0.7887*** (-1.6806)	-0.7612 (-1.4797)
π_4	w_3	0.0332 (0.1937)	-0.0228 (-0.1433)
π_5	w_4	0.0177 (0.1347)	0.0088 (0.0707)
π_{10}	d83	-0.0624 (-0.1408)	-0.0586 (-0.1344)
π_{11}	d84	1.0163** (2.2941)	0.9898** (2.2456)
π_{12}	d85	1.1590* (2.6936)	1.1889* (2.6748)
π_{13}	d86	1.1692** (2.3864)	1.1394** (2.2453)
π_{14}	d87	1.3523** (2.3613)	1.2773** (2.2337)
Variance-Covariance Matrix Parameters			
σ_u^2		0.1088*	0.1199*

Table 3. (Continued) Parameter Estimates by Maximum Likelihood-No Technological Characteristics[1] (Asymptotic t-Ratios)

		Random Firm-Specific Effects	
Parameter	Variable	(5)	(6)
		(7.2282)	(9.6350)
$\sigma^2_{\omega_1}$		0.0022*	0.0023*
		(12.5073)	(12.4275)
$\sigma^2_{\omega_2}$		0.0074*	0.0073*
		(12.3681)	(12.4272)
$\sigma^2_{\omega_3}$		0.0037*	0.0037*
		(12.5482)	(12.5250)
$\sigma_{u\omega_1}$		0.0031	-0.0031**
		(1.0679)	(-2.4509)
$\sigma_{u\omega_2}$		0.0185*	0.0146*
		(5.5209)	(7.1591)
$\sigma_{u\omega_3}$		0.0014	-0.0029**
		(0.6793)	(-1.9800)
$\sigma_{\omega_1\omega_2}$		0.0018*	0.0018*
		(7.2255)	(7.1315)
$\sigma_{\omega_1\omega_3}$		0.0008*	0.0009*
		(4.9548)	(5.0339)
$\sigma_{\omega_2\omega_3}$		0.0009*	0.0009*
		(3.0083)	(2.9561)
σ^2_θ		1.4315*	1.0034*
		(5.7418)	(27.6099)
$\sigma_{\gamma\theta}/\sigma_\gamma\sigma_\theta$		-	0.1912
			(0.6096)
σ_{vu}		-	0.0153
			(0.3629)
$\sigma_{v\omega_1}$		-	0.0115**
			(2.1055)
$\sigma_{v\omega_2}$		-	0.0031
			(0.2930)

Table 3. (Continued) Parameter Estimates by Maximum Likelihood-No Technological Characteristics[1]
(Asymptotic t-Ratios)

		Random Firm-Specific Effects	
Parameter	Variable	(5)	(6)
$\sigma_{\upsilon w_3}$		-	-0.0061 (-0.9692)
σ_γ		0.5021 (1.3054)	0.4554 (1.1407)
Log-likelihood		1037.8977	1046.3812
Nb. of estimated parameters		53	58
Nb. of observations		322	322

1- Only the first-order parameters of the translog are presented here. Complete results may be obtained from the authors upon request.

* Statistically significant at the 1 percent confidence level.

** Statistically significant at the 5 percent confidence level.

*** Statistically significant at the 10 percent confidence level.

Table 4. Technological Measurements at Sample Mean[1]

	Model 1	Model 2	Model 3	Model 4
RTS (Returns to scale)	1.1759	1.1762	1.2149	1.2073
$\dot{T}$ (Technical change)				
1981-82	-0.091	-0.091	-0.095	-0.116
1982-83	-0.475	-0.460	-0.303	-0.317
1983-84	0.027	0.029	0.066	0.078
1984-85	-0.076	-0.074	-0.143	-0.150
1985-86	-0.047	-0.051	-0.040	-0.057
1986-87	0.046	0.056	0.046	0.077
1981-87				
Mean	-0.103	-0.099	-0.078	-0.081
Standard deviation	0.191	0.186	0.136	0.150
Elasticities of Substitution				
ρ^{12}	-1.2741	-0.8827	0.2366	0.4190
ρ^{13}	0.2138	0.2926	0.4943	0.4636
ρ^{23}	0.4435	0.6353	0.7141	0.6914

1- At sample mean: RTS=$1/b_y$, $\dot{T}_t = -(A_t - A_{t-1})/b_y$ and $\rho^{ms} = \frac{c_{ms}+c_m c_s}{c_m c_s}$.

Table 5. Some Second-Order Parameter Estimates (Asymptotic t-Ratios)

Parameter	Variable	*No Firm-Specific Effects* (1)	*No Firm-Specific Effects* (2)	*Random Firm-Specific Effects* (3)	*Random Firm-Specific Effects* (4)
c_{11}	$\frac{1}{2}\tilde{w}_1{}^2$	0.0351* (8.4409)	0.0350* (8.3782)	0.0316* (8.1371)	0.0314* (8.0557)
c_{12}	$\tilde{w}_1\tilde{w}_2$	-0.0062 (-1.4082)	-0.0057 (-1.2849)	-0.0021 (-0.4878)	-0.0015 (-0.3475)
c_{13}	$\tilde{w}_1\tilde{w}_3$	-0.0030 (-1.1013)	-0.0030 (-1.1153)	-0.0019 (-0.6715)	-0.0019 (-0.6620)
c_{22}	$\frac{1}{2}\tilde{w}_2^2$	0.0104 (1.1649)	0.0104 (1.1549)	0.0064 (0.6363)	0.0061 (0.5869)
c_{23}	$\tilde{w}_2\tilde{w}_3$	-0.0083 (-1.6413)	-0.0087*** (-1.7151)	-0.0067 (-1.2071)	-0.0072 (-1.2790)
c_{33}	$\frac{1}{2}\tilde{w}_3$	-0.0121** (-2.5499)	-0.0123** (-2.5870)	-0.0127** (-2.5754)	-0.0130* (-2.5824)
b_{yy}	$\frac{1}{2}\tilde{y}_2$	0.0368** (2.0549)	0.0385** (2.0492)	0.0322 (1.3155)	0.0340 (1.3406)

* Statistically significant at the 1 percent confidence level.
** Statistically significant at the 5 percent confidence level.
*** Statistically significant at the 10 percent confidence level.

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