ESTIMATING THE DEMAND FOR FREIGHT TRANSPORT: THE PRIVATE VERSUS PUBLIC TRADE-OFF IN ANDALUSIAN FOOD INDUSTRY.

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ABSTRACT

Previous work in the demand for freight transportation has focused in the rail-truck substitution problem, leaving aside the prior private versus public trade-off, often found in transportation decision-making. Moreover, those studies that actually examine this alternative selection problem fail to consider the interdependence between the transport type choice and the shipment size decision. The purpose of this paper is to analyze shippers' behavior. Particular attention is paid to, first, the public-private trade-off and, second, the simultaneity of alternative selection and shipment size choice. In order to provide a quantitative evaluation, as an illustrative case, the theoretical model developed is tested on data gathered by means of a sample survey conducted to Andalusian enterprises belonging to the food industry.

JEL classification: R410: Transportation: Supply, Demand and Congestion. C350: Econometric Methods: Multiple/Simultaneous Equation Models: Truncated and Censored Models.

1.- INTRODUCTION

Domestic freight transport in Andalusia takes place mostly by road. Its market share goes from 97%, when measured in terms of total tons, to 91%, when ton-kilometers are considered. Tables 1 and 2 present the relative weights of different transport modes for five broad commodity classes.

As can be seen, road's supremacy is completely out of the question. Only for chemical and petroleum products does truck transport have some competition from pipelines and maritime transport. Remaining product classes show a total dependence on road transport.

Nevertheless, most freight transport demand studies investigate the rail-truck substitution problem. Considerably less effort can be found analyzing the determinants of road transport, specifically relating to the choice between private -own account- transport and public –purchased- transport. This is in marked contrast with present passenger demand modelling, where the paradigm has been the investigation of the public versus private trade-off, prior to the study of transport mode choice.[1]

Moreover, those studies that actually examine this alternative selection problem, from the freight perspective, fail to consider the interdependence between the transport type choice and the shipment size decision.[2] Only the first issue is addressed, so that logistic concerns, and its influence on transport-related behavior, are simply disregarded.

The purpose of this paper is to analyze the freight transportation decision-making process. Given the above dissertation, particular attention is paid to, first, the public-private trade-off and, second, the simultaneity of alternative selection and

[1] See, for instance, Ben Akiva and Learman (1985, pp.276-321, 323-372), Ortúzar and Willumsen (1990, pp.179-198) or Matas (1991).

shipment size choice. In order to provide a quantitative evaluation of shippers' behavior, as an illustrative case, the theoretical model developed is tested on data gathered by means of a sample survey conducted to Andalusian enterprises belonging to the food industry.

The study is organized as follows. Section 2 presents a review of existing approaches towards modelling the demand for freight transport. Section 3 introduces the theoretical model. Section 4 discusses the econometric model to be used in the empirical analysis. The data and variable construction are described in section 5. Empirical results are given in section 7. And finally, section 8 debates possible improvements and conclusions.

TABLE 1.- MARKET SHARE OF DIFFERENT TRANSPORT MODES FOR COMMODITY CLASSES. TRAFFIC FLOWS MEASURED IN TONS.

Source: Encuesta Permanente del Transporte por Carretera and unpublished data supplied by RENFE and CLH. S.A.

	ROAD	RAIL	PIPE	SEA	TOTAL
Food and agricultural products	97.03	0.44	-	2.53	100.00
Construction and mineral fuels	99.05	0.36	-	0.59	100.00
Chemical and petroleum products	89.48	1.50	3.97	5.06	100.00
Metal products	98.00	0.82	-	1.18	100.00
Machines, vehicles and other products	97.73	0.54	-	1.73	100.00
TOTAL	97.23	0.56	0.45	1.76	100.00

TABLE 2.- MARKET SHARE OF DIFFERENT TRANSPORT MODES FOR COMMODITY CLASSES. TRAFFIC FLOWS MEASURED IN TON-KILOMETERS.

Source: Encuesta Permanente del Transporte por Carretera and unpublished data supplied by RENFE and CLH. S.A.

	ROAD	RAIL	PIPE	SEA	TOTAL
Food and agricultural products	92.21	1.47	-	6.32	100.00
Construction and mineral fuels	94.11	1.25	-	4.63	100.00
Chemical and petroleum products	74.67	5.05	5.31	14.96	100.00
Metal products	94.03	3.20	-	2.77	100.00
Machines, vehicles and other products	95.65	0.72	-	3.63	100.00
TOTAL	91.16	1.89	0.72	6.23	100.00

[2] Examples can be found in Winston (1981) and, more recently, Jiang et al. (1999).

2.- THE DEMAND FOR FREIGHT TRANSPORTATION: THE STATE OF THE ART

According to Kanafani (1983, p.280), there are three basic approaches to the analysis of commodity transportation demand: the input-output approach, spatial interaction modeling and the microeconomic perspective.

In the first case, interrelations between sectors of an economy are analyzed. With transportation identified as one of the sectors, it becomes possible to investigate transportation requirements of the other sectors and to translate those into flows of goods. The multiregional models of Leontieff and Strout (1963) or Liew and Liew (1985) are qualified samples of this kind of analysis.

The second approach of spatial interaction modelling is aggregate in nature. Surpluses and deficits of commodities are located at various points of space and a process is then postulated whereby flows of commodities occur from points of excess supply to points of excess demand. Generally, the transportation system is explicitly represented by a network, with its nodes and arcs, and considerable effort is placed on assigning traffic flows to that network. To this group belong studies like the seminal Harvard-Brookings model of Kresge and Roberts (1971) or, more recently, Harker's (1987) generalized spatial price equilibrium model.

Finally, we find the microeconomic approach, also called econometric, in which the basic decision unit of analysis is the firm, considered the potential user of transportation. In this approach, the demand for freight transportation is derived by considering transportation as one of the inputs into the production or marketing process of the firm. Cross-section or longitudinal data relating to different enterprises or producing sectors are used to develop structural relationships describing shipper's behavior. Let us review this last perspective in more detail.

Following Winston (1983), microeconomic models can be classified into aggregate and disaggregate, depending on the nature of the data employed. In the aggregate studies, the data consists of total flows by mode at the regional or national level. In the disaggregate studies, the data consists of information relating to individual shipments.

In general, aggregate models have tended to be based on cost minimizing behavior by firms. Good examples can be found in Oum (1979a, 1979b), Friedlaender and Spady (1980), or, lately, Bianco, Campisi and Gastaldi (1995). Although, from a theoretical point of view, disaggregate models seem preferable to aggregate ones, in particular contexts, aggregate models can turn more useful than their disaggregate counterparts. Especially, if cost limitations preclude an adequate sampling of the population of a large-scale policy analysis, an aggregate methodology can become the best choice on practical grounds.

Notwithstanding, disaggregate models hold a number of important conceptual strengths (Small and Winston, 1999). First, the number of observations is much larger, leading to more precise estimates of parameters. Second, the disaggregate approach is conducive to much richer empirical specifications, thus better capturing the variation in characteristics of the shipper. Finally, dissagregate models do not require the unrealistic assumption of identical decision-makers as aggregate models do. Therefore, one can conclude that the dissagregate methodology should be used whenever possible.

In the literature, dissagregate models are, in turn, classified as behavioral and inventory (Winston, 1983 and Zlatoper and Austrian, 1989). In the first case, the decision-maker is the physical distribution manager of the receiving or shipping firm. It is assumed that shipment size, dependent on the purchasing department, is exogenous to this agent. In consequence, only mode choice is modelled. Given there is uncertainty relative to the quality of service effectively obtained, the shipper is postulated to maximize his expected utility from his choice of mode. Empirically, a random expected utility model is used.

The inventory-based models, on the other hand, attempt to analyze freight demand from the perspective of the logistic manager. As first noted by Baumol and Vinod (1970), freight in transit can be considered to be an inventory on wheels. Accordingly, in-transit carrying costs and inventory costs must be added to direct transport costs in order to attain an adequate picture of the options opened to the decision-maker. From this point of view, the logistic manager faces a trade-off as a greater shipment size probably diminishes unit transport costs but, in turn, it implies a larger stock for the good in question.

The models contained in Winston (1981), Daughety and Inaba (1978, 1981), Ortúzar (1989) or Jiang, Johnson and Calzada (1999) constitute applied examples of the behavioral approach. Lately, neverhteless, empirical work has tended to be based on the inventory-theoretic framework. The initial models of Roberts (1977) and Roberts and Chiang (1984) considered only discrete options; the paradigm is now the joint estimation of discrete and continuous choices, first considered by McFadden, Winston and Boersch-Supan (1985). Later refinements of this original model can be found in Inaba and Wallace (1989), Abdelwahab and Sargious (1992), Genç, Inaba and Wallace (1994) or Abdelwahab (1998).

3.- A FREIGHT TRANSPORT DEMAND MODEL

The demand is a relationship between quantity wanted and its determinants. For freight transport, one needs to know the variation in traffic volumes due to variations in prices, quality of service, distance served,..

In this paper, we analyze the demand for freight transport from the perspective of an inventory manager, who wishes to minimize the total logistics costs that his firm incurs in the short run. It is assumed that all long and medium run decisions, like location, firm size, level of production or marketing policy, have already been taken. Furthermore, it is stated that the choice of supplier - or client, depending on the cases – is also given, due to routine, dependence, or the existence of a long-run provision contract. Accordingly, in the tradition of the inventory-based approach, the model presented here simultaneously considers two transport-related decisions: transport-type alternative and shipment size.

Most empirical studies, belonging to this approach, take into account two main options: road versus rail transport. In Andalusia, that trade-off is practically nonexistent, given road's hegemony for freight transport, as stated previously. However, most shippers do have a choice relative to purchasing the transport services outside the firm or providing them internally. This choice has not yet been dealt with, in the literature, from the perspective of the logistic manager of the firm. Our model attempts to achieve that goal.

It is assumed that the inventory manager wishes to minimize total logistic costs of the firm. He controls two decision variables: shipment size and transport-type alternative – either own account or purchased transport.

Following Baumol and Vinod (1970), it can be stated that total logistic costs consist of direct shipping costs, in-transit carrying costs, ordering costs and storage costs. Direct shipping costs depend on transport rates and the amount shipped. In-transit carrying costs turn up because of the possible reduction of value of the good while in transit plus the interest one must satisfy on the capital tied. Basically, they depend on the good's value and transit time. Ordering costs are a function of the number of shipments, which, given total annual amounts, is function of shipment size. Finally, storage costs depend on the good's value, average shipment size, and uncertainty relative to product demand and transit time.

If we consider two main transport options, private and public transport, it may be assumed that the inventory manager computes optimal shipment size for each alternative and chooses that which minimizes total logistic costs. Formally, let *C(i,X)* be the logistics costs function, whose value depends on shipment size *X* and the alternative selected *i*. We can the denote by C^* the optimized function, that is:

$$C^* = \min_i \min_X C(i, X) \qquad [1.]$$

This optimized function depends on a series of exogenous variables that can be listed under the following headings:

- Transport-type characteristics, **s**, such as rates, transit time or reliability of the two alternatives.
- Commodity attributes, $\mathbf{s^k}$, such as its value, density or state.
- Market characteristics, $\mathbf{s^m}$, such as total annual quantity transported or spatial influence zone.

Consequently, the optimized logistic costs function becomes:

$$C^* = C^*(\mathbf{s}, \mathbf{s^k}, \mathbf{s^m}) \qquad [2.]$$

where it is assumed that transport-type choice and shipment size selection are both dependent on transport-type characteristics, commodity attributes and market conditions.

4.- A MIXED CONTINUOUS/DISCRETE CHOICE ECONOMETRIC MODEL OF TRANSPORT DEMAND

In the real world, the analyst is likely to fail to observe all factors influencing transport behavior. Besides, observed variables may contain measurement errors. Therefore, the optimized transport costs function depends not only on the observed exogenous variables, but also on an unobservable error term.

$$C^* = C^*(\mathbf{s}, \mathbf{s^k}, \mathbf{s^m}, \varepsilon) \qquad [3.]$$

For each transport alternative, there is an optimal shipment size which direct or indirectly relies on the preceding variables:

$$X_i^* = X_i^*(\mathbf{s_i}, \mathbf{s^k}, \mathbf{s^m}, \varepsilon) \quad i=1,2 \qquad [4.]$$

This can be approximated by a linear functional form in the following way:

$$X_i^* = \beta_{0i} + \boldsymbol{\beta_{1i}}\mathbf{s_i} + \boldsymbol{\beta_{2i}}\mathbf{s^k} + \boldsymbol{\beta_{3i}}\mathbf{s^m} + \varepsilon_i \qquad i=1,2 \qquad [5.]$$

Conditional on **s**, $\mathbf{s^k}$, and $\mathbf{s^m}$, the firm is observed to ship X_1^* if $C(1, X_1^*) < C(2, X_2^*)$. In order to ease model estimation, an index I^* can be constructed representing the amount of cost savings obtained by choosing one transport alternative over the other. That is, alternative 1 (public transport) is chosen if the index is positive and alternative 2 (private transport), when it is negative. Formally:

$$I^* = C(2, X_2^*) - C(1, X_1^*) \qquad [6.]$$

From the analyst's point of view, this index's value cannot be known, only its sign can. The index relies on the exogenous variables found for the logistics costs function and on the endogenous shipment size variables. For the same reasons stated above, also an error term appears.

$$I^* = I^*(\mathbf{s}, \mathbf{s^k}, \mathbf{s^m}, X_1^*, X_2^*, \nu) \qquad [7.]$$

Approximating by a linear function:

$$I^{*} = \delta_0 + \delta_{\mathbf{1}}\mathbf{s} + \delta_{\mathbf{2}}\mathbf{s}^{\mathbf{k}} + \delta_{\mathbf{3}}\mathbf{s}^{\mathbf{m}} + \eta_1 X_1^{*} + \eta_2 X_2^{*} - \nu \qquad [8.]$$

As a result, the econometric model to be used in the empirical analysis is completely specified by the following system of simultaneous equations:

$$X_1^{*} = \beta_{01} + \beta_{\mathbf{11}}\mathbf{s}_1 + \beta_{\mathbf{21}}\mathbf{s}^{\mathbf{k}} + \beta_{\mathbf{31}}\mathbf{s}^{\mathbf{m}} + \varepsilon_1 \qquad [9.]$$

$$X_2^{*} = \beta_{02} + \beta_{\mathbf{12}}\mathbf{s}_2 + \beta_{\mathbf{22}}\mathbf{s}^{\mathbf{k}} + \beta_{\mathbf{32}}\mathbf{s}^{\mathbf{m}} + \varepsilon_2 \qquad [10.]$$

$$I^{*} = \delta_0 + \delta_{\mathbf{1}}\mathbf{s} + \delta_{\mathbf{2}}\mathbf{s}^{\mathbf{k}} + \delta_{\mathbf{3}}\mathbf{s}^{\mathbf{m}} + \eta_1 X_1^{*} + \eta_2 X_2^{*} - \nu \qquad [11.]$$

This is the switching regression model with endogenous switching considered by Maddala (1983, pp.223-28) and Greene (1999, pp.839-848). In our particular case, the criterion function corresponds to equation [11] and the two possible regimes to equations [9] and [10].

As it can be observed, the criterion function depends on the endogenous variables X_1^{*} and X_2^{*}. In order to estimate equation [11] as a binary choice model, we must transform it into an equation which consists of only predetermined variables. This can be achieved by substituting the values of X_1^{*} and X_2^{*} from equation [9] and [10] into equation [11] to get the reduced form equation. The final specification of the model is thus:

$$X_1^{*} = \beta_{01} + \beta_{\mathbf{11}}\mathbf{s}_1 + \beta_{\mathbf{21}}\mathbf{s}^{\mathbf{k}} + \beta_{\mathbf{31}}\mathbf{s}^{\mathbf{m}} + \varepsilon_1 \qquad [12.]$$

$$X_2^{*} = \beta_{02} + \beta_{\mathbf{12}}\mathbf{s}_2 + \beta_{\mathbf{22}}\mathbf{s}^{\mathbf{k}} + \beta_{\mathbf{32}}\mathbf{s}^{\mathbf{m}} + \varepsilon_2 \qquad [13.]$$

$$I^{*} = \theta_0 + \theta_{\mathbf{1}}\mathbf{s} + \theta_{\mathbf{2}}\mathbf{s}^{\mathbf{k}} + \theta_{\mathbf{3}}\mathbf{s}^{\mathbf{m}} - \varepsilon \qquad [14.]$$

The error terms in these equations are correlated. Consequently, joint estimation of the system of equations is required. In this paper, we will follow the method suggested by Lee and Trost (1978) of previously computing a two-stage least squares estimation and using the results obtained as starting values for the maximum likelihood procedure.

The initial two-stage least squares technique is frequently referred to as 'Heckit method',[3] in the literature. Basically, a maximum likelihood probit is applied to estimate the alternative criterion function in the first stage, and ordinary least-squares is used to adjust the shipment size equations in the second stage.

Following Abdelwahab and Sargious (1992), it is assumed that the residuals $\varepsilon_1, \varepsilon_2$ and ε in the system of equations [12-14] are serially independent and have a trivariate normal distribution with mean vector **0** and non-singular covariance matrix $\sum$,[4]

$$\sum = \begin{bmatrix} \sigma_{\mathbf{1}}^{\mathbf{2}} & \sigma_{12} & \sigma_{1\varepsilon} \\ \sigma_{12} & \sigma_2^{\mathbf{2}} & \sigma_{2\varepsilon} \\ \sigma_{1\varepsilon} & \sigma_{2\varepsilon} & 1 \end{bmatrix} \qquad [15.]$$

Equations [12] and [13] cannot be estimated by ordinary least squares because the conditional expectations of the residuals are non-zeros; that is, $E(\varepsilon_1 \mid I) \neq 0$ and $E(\varepsilon_2 \mid I) \neq 0$. Since sample separation is observed, we have the observations I_t. Thus, we can apply the maximum likelihood procedure to estimate the reduced-form parameters of the probit model, in what constitutes the first stage:

$$I^* = \theta_0 + \theta_{\mathbf{1}}\mathbf{s} + \theta_{\mathbf{2}}\mathbf{s}^{\mathbf{k}} + \theta_{\mathbf{3}}\mathbf{s}^{\mathbf{m}} - \varepsilon \qquad [16.]$$

[3] Apparently, a first version of the procedure was presented by Heckman (1976) "The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models", Annals of Economic and Social Measurement vol.5, pp.475-492, cited by Maddala (1983, p 221).

[4] Note that σ_ε^2 has been normalized to one. That can be done without loss of generality (Abdelwahab and Sargious, 1992).

With these estimates $\hat{\theta}_0$ $\hat{\theta}_1, \hat{\theta}_2$ and $\hat{\theta}_3$ in hand, one can calculate the selectivity correction factors $\hat{W}_1$ and $\hat{W}_2$ as:[5]

$$\hat{W}_1 = \frac{\phi\left(\hat{\theta}_0 + \hat{\theta}_1 \mathbf{s} + \hat{\theta}_\mathbf{2} \mathbf{s}^\mathbf{k} + \hat{\theta}_3 \mathbf{s}^\mathbf{m}\right)}{\Phi\left(\hat{\theta}_0 + \hat{\theta}_1 \mathbf{s} + \hat{\theta}_\mathbf{2} \mathbf{s}^\mathbf{k} + \hat{\theta}_3 \mathbf{s}^\mathbf{m}\right)} \quad [17.]$$

$$\hat{W}_2 = \frac{\phi\left(\hat{\theta}_0 + \hat{\theta}_1 \mathbf{s} + \hat{\theta}_\mathbf{2} \mathbf{s}^\mathbf{k} + \hat{\theta}_3 \mathbf{s}^\mathbf{m}\right)}{1 - \Phi\left(\hat{\theta}_0 + \hat{\theta}_1 \mathbf{s} + \hat{\theta}_\mathbf{2} \mathbf{s}^\mathbf{k} + \hat{\theta}_3 \mathbf{s}^\mathbf{m}\right)} \quad [18.]$$

And then, these expressions can be appended to equations [12] and [13] so that:

$$X_1^* = \beta_{01} + \beta_{\mathbf{11}} \mathbf{s}_1 + \beta_{\mathbf{21}} \mathbf{s}^\mathbf{k} + \beta_{\mathbf{31}} \mathbf{s}^\mathbf{m} - \sigma_{1\varepsilon} W_1 + \zeta_1 \quad [19.]$$

$$X_2^* = \beta_{02} + \beta_{\mathbf{12}} \mathbf{s}_2 + \beta_{\mathbf{22}} \mathbf{s}^\mathbf{k} + \beta_{\mathbf{32}} \mathbf{s}^\mathbf{m} + \sigma_{2\varepsilon} W_2 + \zeta_2 \quad [20.]$$

The second stage involves adjusting these two equations. The first one [equation 19] can be estimated by ordinary least squares from sample observations on purchased transport, as $E(\zeta_1 \mid I = 1) = 0$. Similarly, equation [20] becomes estimable by ordinary least squares from sample observations on own-account transport, given $E(\zeta_2 \mid I = 0) = 0$.

According to Lee and Trost (1978), the resulting estimates of this ‘Heckit method’ are consistent, but not efficient. In order to obtain efficient estimators, maximum likelihood procedures must be implemented.

For the estimation of the simultaneous equation model of equations [12] to [14], the likelihood function is given by:

[5] These factors are obtained from the properties of truncated normal variables. Maddala (1983, p.224) explains the calculations involved.

$$L = \prod_t \left[\int_{-\infty}^{\theta_0+\theta_1\mathbf{s}+\theta_2\mathbf{s^k}+\theta_3\mathbf{s^m}} g\left(X_1^* - \beta_{01} - \beta_{11}\mathbf{s_1} - \beta_{21}\mathbf{s^k} - \beta_{31}\mathbf{s^m}, \varepsilon_t\right) d\varepsilon_t \right]^{I_t} \left[\int_{\theta_0+\theta_1\mathbf{s}+\theta_2\mathbf{s^k}+\theta_3\mathbf{s^m}}^{\infty} f\left(X_2^* - \beta_{02} - \beta_{12}\mathbf{s}_2 - \beta_{22}\mathbf{s^k} - \beta_{32}\mathbf{s^m}, \varepsilon_t\right) d\varepsilon_t \right]^{1-I_t} \quad [21.]$$

where *g* represents the joint normal density function of ε_{1t} and ε_t and *f* stands for the corresponding function of ε_{2t} and ε_t.

As stated by Abdelwahab and Sargious (1992), the resulting function is highly non-linear and thus difficult to optimize. However, the estimates obtained by the previously presented 'Heckict method' may be used as initial values of the parameters, turning convergence more likely.

5.- DATA AND VARIABLE CONSTRUCTION

As already stated, the data used in the empirical analysis were collected from a questionnaire survey conducted, in 1999, on a sample of Andalusian agro-industrial enterprises. The sample population was taken from the business directory of the Central de Balances, Junta de Andalucía.[6]

Every respondent was requested to provide information on characteristics of his enterprise, characteristics of his main product and characteristics of the transport service used for most shipments of that product.

The resulting database contains 106 observations, representing the corresponding number of typical shipments encountered in the food sector. Of these, 59 cases relate to public transportation and 47, to private transportation. For each one, a set

[6] Instituto de Fomento de Andalucía et al. (1999), Central de Balances de Andalucía..., pp.1-1205.

of features is recorded, basically transport-type attributes, commodity characteristics and market conditions.

The variable SIZE refers to the amount transported, measured in weight units, in an individual shipment. ACCOUNT records whether the freight service is purchased (value 1) or provided internally (value 0).

The variables characterizing the good transported include: VALUE, in monetary units per unit of weight; PERISHABLE, a dummy variable (1 if the good is perishable, 0 otherwise); ALIVE, a dummy variable (1 if the merchandise consists of live animals, 0 otherwise); and RELATION, also a dummy variable (1 if the commodity is an output, 0 when it corresponds to an input).

Three market characteristics are considered: the frequency of shipments, total sales and the scope of business. The variable FREQUENCY stands for the annual number of shipments that the company makes to its most frequent destination. It is intended to capture the probability of a stable relationship with its clients. SALES records total revenue of the firm. It is a measure of firm's size. The scope concept is instrumented by means of three, mutually excluding, dummy variables. The variable LOCAL takes value 1 for those commercial relationships belonging to a local or provincial level. The variable REGIONAL takes value 1 for those relating to Andalucía. Ultimately, the variable SUPRA takes value 1 when the commercial relationship belongs to the national or international level. Obviously, to avoid perfect collinearity, one of the three variables must be left out of the model.

Finally, two transport-type attributes are included: time and cost.[7] The variable TIME measures the duration of transport. For each shipment, the variable COST1

[7] Respondents were also asked about the variability of transport time but the quality of the data obtained was very poor.

registers expenses for purchased transport and COST2, for own account transport. For each observation, one of these values is real and one is estimated.[8]

Table 3 presents a description of these variables for own account and purchased shipments, as well as for the entire data set.

TABLE 3.- DESCRIPTION OF THE AVAILABLE VARIABLES				
Source: Mail questionnaire. Calculations performed using LIMDEP, version 7.0.				
		MEAN (STANDARD DEVIATION)		
VARIABLE	UNIT	PURCHASED	OWN ACCOUNT	TOTAL
ACCOUNT	0/1			0.56 (0.49)
SIZE	Tons	16.20 (14.58)	9.39 (7.31)	13.18 (12.35)
VALUE	Ptas/kg	513.35 (1071.42)	442.64 (616.62)	481.32(891.71)
PERISHABLE	0/1	0.42 (0.49)	0.59 (0.49)	0.50 (0.50)
ALIVE	0/1	0.13 (0.34)	0.06 (0.24)	0.10 (0.30)
RELATION	0/1	0.45 (0.50)	0.80 (0.39)	0.61 (0.48)
FREQUENCY	N/year	257.93 (490.05)	288.88 (513.44)	271.66 (498.36)
SALES	Thous. Ptas.	4395.50 (11285.14)	1315.78 (3841.13)	3029.97 (8898.03)
LOCAL	0/1	0.10 (0.30)	0.31 (0.47)	0.19 (0.40)
REGIONAL	0/1	0.38 (0.49)	0.44 (0.50)	0.41 (0.49)
SUPRA	0/1	0.38 (0.49)	0.23 (0.42)	0.32 (0.46)
TIME	Days	2.39 (7.95)	0.54 (0.59)	1.57 (5.99)
COST1	Thous. Ptas.	68.24 (76.67)	47.88 (8.43)	59.21 (58.15)
COST2	Thous. Ptas.	72.89 (82.17)	31.51 (33.56)	54.54 (68.19)
DISTANCE	Km.	658.22 (1160.10)	211.72 (209.01)	460.24 (901.23)
N. Observations		59	47	106

At a first sight, the variables behave differently for the two options considered. Except for one of the variables – frequency - both average values and data dispersion are larger for the public transport alternative than for the private one.

[8] For those shipments taking place by public transport COST2 was calculated as
COST2=17078,21-14206,81*REGIONAL+1,86*SALES+20817,11*PERISHABLE
-16,16*FREQUENCY+5,20*DISTANCY*SIZE. R^2=.45 (n=47)
For those shipments taking place by private transport COST1 was estimated as:
COST1=32926,43+31,52*DISTANCY+494,33*SIZE
+0,31*DISTANCY*SIZE R^2=.99 (n=62)

6.- ESTIMATION RESULTS

Equations [12], [13] and [14] were estimated simultaneously by the maximum likelihood method. As Lee and Trost (1978) suggest, to get starting values for this routine, the system of equations was first estimated by the two-stage least squares method - known as 'Heckit' method - previously described.[9] Final specification of the model was achieved by testing minor changes in the choice of explanatory variables. All of them were subject to a cause and effect relationship with the dependent variables, but some simply could not be included simultaneously due to its mutually high correlation.[10] This last arrangement obtained the lowest value of the Akaike information criterion.[11]

The results of the estimations are presented in table 4. To economize on space, only the maximum likelihood estimates are reported. Nevertheless, it should be mentioned that the 'Heckit' estimates of the model's coefficients were relatively similar in magnitude to those obtained by the maximum likelihood method.

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9 All the calculations were performed using the LIMDEP package, version 7.0. We thank Prof. Dr. Manuel Jaén for providing us with a copy of this software.

10 That was the problem encountered between the variables distance and travel time. Only the last one was finally chosen.

11 This measure is explained, for instance, in Cabrer Borrás et al. (2001, p.138).

TABLE 4.- ESTIMATION RESULTS. MAXIMUM LIKELIHOOD METHOD				
Source: Mail questionnaire. Calculations performed using LIMDEP, version 7.0				
Dependent variable: SIZE NOBS=106				
Log likelihood function= -419.7592| Akaike Infomation Criterion= 8.3728				
Selection equation for ACCOUNT				
Variable	Coefficient	Standard Error	Coef./Stand. Er.	Probability
CONSTANT	0.5952	0.5918	1.006	0.3145
RELATIÓN	-0.7218	0.4183	-1.726	0.0844
PERISABLE	-0.06998	0.4216	-1.660	0.0970
ALIVE	0.5751	0.6285	0.915	0.3602
VALUE	0.23E-04	0.16E-03	0.089	0.9293
FREQUENCY	-0.56E-03	0.15E-02	-0.362	0.7174
LOCAL	-0.7090	0.6971	-1.017	0.3091
TIME	0.0477	0.3637	0.131	0.8956
COST1	-0.70E-02	0.94E-02	-0.747	0.4552
COST2	0.0155	0.45E-02	3.446	0.0006
Equation for variable SIZE, public transport alternative				
CONSTANT	24.8977	4.6506	5.354	0.0000
RELATION	-8.6859	6.9171	-1.256	0.2092
ALIVE	-9.5166	8.1424	-1.169	0.2425
TIME	-0.5342	0.4821	-1.108	0.2678
COST1	0.0508	0.0270	1.878	0.0604
Equation for variable SIZE, private transport alternative				
CONSTANT	-8.8260	5.2187	-1.691	0.0908
RELATION	-8.9874	3.3929	-2.649	0.0081
FREQUENCY	-3.2641	3.2085	-1.017	0.3090
VALUE	-3.6501	1.6116	-2.265	0.0235
COST2	0.6046	0.1102	5.482	0.0000
Variance parameters[12]				
σ_1	5.1306	0.8420	6.093	0.0000
$\rho_{1\varepsilon}$	0.4169	0.4844	0.861	0.3894
σ_2	14.0601	1.4733	9.546	0.0000
$\rho_{2\varepsilon}$	0.8350	0.1561	5.369	0.0000

As already stated, the joint estimation of the system of equations [12], [13] and [14] is founded in the hypothesis of interdependence between the two decisions on transport-type and shipment size. From an econometric point of view, this circumstance implies the existence of a strong correlation between the error term in the reduced form criterion equation (equation [14]) and the error terms in both the shipment size equation for public transport (equation [12]) and the corresponding equation for private transport (equation [13]). Consequently, the adequacy of the model developed is tested by the significance of the estimated values of $\rho_{1\varepsilon}$, the correlation between ε_1 and ε, and $\rho_{2\varepsilon}$, the correlation between ε_2 and ε. As can be observed in table 4, $\rho_{1\varepsilon}$ - contrary to $\rho_{2\varepsilon}$ - does not appear to be very significant. Thus, our initial theoretical premises of joint selection of transport-type and shipment size is only confirmed for private transport, but not for public transport.

Turning to the rest of the model's parameters, and considering in the first place the results obtained for the criterion function, one can conclude that, in general, all the estimates are of expected sign and seem to be of plausible magnitude. Nevertheless, some of the variables, like 'value', 'frequency' or 'time', are not very significant. From the econometric point of view, they should have been eliminated of the final specification. However, theoretically, if they were part of the shipment size equations, they had to be part of the reduced form of the criterion function too.

The positive sign of the constant indicates that, all else equal, shippers have an inherent preference for public transport over private. Relative to the four commodity characteristics included, one can say that own-account transport is preferred for the shipment of outputs, rather than inputs, and if the good is perishable; but public transport is favored over private transport for moving living animals or commodities of higher values. As for the market characteristics, own-account transport is most preferred when there is a stable relationship with the destination or for commercial relations pertaining to the local market. Finally, turning to the transport attributes, one can comment that purchased transport is chosen more frequently the longer the trip, the smaller its cost and the greater the cost of the alternative own-account transport.

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[12] Given the variance of ε is one, the correlation between ε_1 and ε is $\rho_{1\varepsilon} = \sigma_{1\varepsilon} / \sigma_1$. Equally, the

The interpretation of the estimates relative to the shipment size equations must be made taking into account the results corresponding to the criterion function, at the same time. For the public transport equation, the negative sign in the variables ‘relation’ or ‘alive’ means shipment size is smaller for outputs, compared to inputs, and for the movement of living animals; the negative sign in the variable ‘time’ suggests that, once purchased transport is selected, load size diminishes with transport duration; the positive sign in the variable ‘cost’ implies that, once purchased transport is selected, the transport cost increases with shipment size.

Considering now the private transport alternative, its shipment size equation reveals that, again, shipment size is smaller for outputs, compared to inputs. It also shows an expected result for the variables ‘value’ and ‘frequency’. Shipment size increases with decreases in commodity value and the more frequent the shipments, the smaller the shipment size. Finally, as for public transport, once own account transport is chosen, the cost of the service increases with the size of the load.

7.- CONCLUDING OBSERVATIONS

In line with the works of McFadden, Winston and Boersch-Supan (1985), Inaba and Wallace (1989) or Abdelwahab and Sargious (1992), our theoretical model of freight demand clearly states that the transport-type choice and the shipment-size decision are generated from the same optimization problem. From a statistical point of view that requires the joint estimation of the equation governing the transport-alternative selection together with the equations relative to the shipment size for each option.

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correlation between ε_2 and ε is $\rho_{2\varepsilon} = \sigma_{2\varepsilon} / \sigma_2$. Thus $\sigma_{1\varepsilon} = \rho_{2\varepsilon}\sigma_2$ and $\sigma_{2\varepsilon} = \rho_{2\varepsilon}\sigma_2$.

Following Lee and Trost (1978), the system of equations can be estimated by maximum likelihood taking as starting values the estimates obtained by the 'Heckit' method. This combined procedure turns convergence of the process of maximization more likely.

Both the empirical model and the method of estimation are tested in data gathered by means on a sample survey conducted on agro-industrial Andalusian enterprises. The empirical implementation of the model indicates the statistical necessity of jointly estimating the three equations considered. The empirical findings show that, all else equal, public transport is favored over private transport and that the probability of selecting purchased transport increases with transport costs and travel time.

Further work is clearly needed in order to extrapolate the empirical results of the present paper. As already stated, most studies of the logistics approach analyze the truck versus rail trade-off and therefore we lack adequate parameters of comparison. The most interesting options would be the investigation of freight transport demand for other industrial sectors in Andalusia or the analysis of agro-industrial shippers' behavior for other geographical regions.

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LIMDEP estimates these parameters separately. And that is the information presented here.

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