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A logistic distribution model of new short sea shipping line along a mutimodal corridor in Italy

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Abstract

The purpose of the application focuses on an intermodal model (RPL) to simulate the transport choice for freight sending on the most relevant corridor Naples–Milan. In this, operate a rail- road system with the introduction a new short sea shipping (SSS) intermodal line (Naples Sea Genova road Milan). The paper considers a collaboration with a multimodal transport operator, with many logistic platforms in Italy to analyze the degree of competition inside corridor. An application along this very congested route Milan (Segrate interport) - Nola (Naples interport) was used**.** The econometric models applied to operator choices are a random parameter logit model vs multinomial logit model with frequency, type of load and cost as main parameters.

Keywords: random parameter model, short sea shipping, intermodal corridor

1. Introduction

Freight logistics distribution is essentially focused on the choice of the mode of transport, and its characteristics of shipping and handling of goods. The problem of modal rebalancing and of the greater integration between means and networks (combined transport) is always current and in turmoil as one of the crucial issues is represented by reducing the competitive gap between road transport and rail transport. Italy is experiencing a cyclical crisis that sees a significant decline in logistics companies, especially in transport, with a decrease in haulers' and warehouse managers. Companies operating in third party logistics are currently just over 97,000. The paper studies the logistic distribution of an intermodal freight transport leader, Terracciano Group, which is based in the Campania Region and operates from Nola's interport on a global level in Italy with 20 logistics platforms, 200 trailers and 550 swap bodies throughout Italy. The analysis concerns road transport, rail transport and the combined sea-road NA-GE- MI along the Nola-Milan route. This is one of the most important logistics corridors in the country with a high added value and a growing trend in traffic in both directions. Then, great attention must be paid to the distribution of goods in the last mile of the corridor with "green" initiatives, and for the urban connection, the delivery of the product take place with cargo-bikes and electric vehicles. Terracciano Group is also characterized by a series of technological and digital innovations such as workflow scheduling (for the optimal management of resources within distribution centers), *load building* (for the calculation of the volumetric size of orders and for the planning of order preparation and travel activities), *RFID* (for the optimization of picking and storage operations), *GPS systems* (for the management of the vehicle fleet and for the consolidation and sorting of pallets / packages) and the *logistics APP* (for support in relations with carriers via mobile internet applications).

The purpose of the application focuses on a logistic-consignment model, which simulates the transport service for each shipment, along multimodal corridor considering land transport and short sea shipping, with frequency of consignment, reliability, logistic cost, the type of load etc. The econometric model applied to modal choices is the random parameter logit (mixed logit model) compared to multinomial logit model.

The random parameter logit (mixed logit) approach has been present in the literature, (Train 2009; Hensher and Greene 2003), for ordinal (Falco et al. 2015; Greene and Hensher 2010b) and for count models (Gourieroux et al. 1984; Greene 2007; Anastasopoulos and Mannering 2009. For the most relevant codes available (MXLB+GAUSS) Train (2019) and LIMDEP - NLOGIT (Greene 2015 a,b) based on Maximum Likelihood Simulation (MLS) approach. Actually is available a RCore Team package as (Sarrias 2016) application with estimated (MLS) as (Train 2015) .

In order to capture individual heterogeneity of each variable used in this work (coefficient) we assume its varies randomly across observations with random utility maximization-RUM, with simulated maximum likelihood method (McFadden 1974). Since the distribution is unknown , this type of individual heterogeneity it is usually labeled as 'unobserved heterogeneity' represented by the mean and variance of the coefficient.

2. Multimodal distribution logistic model

The typology of the logistic distribution models for the simulation of the choice of the mode of transport of goods can be divided into two sectors: consignment models that simulate the choice of the mode for each single shipment and logistic models that simulate integrated sequence of logistic choices among which the dimension, the frequency of the consignments, the dangerousness of the cargo, Ben-Akiva M., & de Jong G. (2008).

The consignment models are by far the most used; they have belonged to the family of logit models more often multinomial logit, Ben Akiva M. and Lerman S., (1987). The choice alternatives usually correspond to the transport modes to be analyzed for a given shipment, Freight Transportation Group, MIT (1980). Same recent logistics models are also used to evaluate the supply strategies. These disaggregated models simulate the choice of the mode of transport both by the vendors and buyers and the related logistic-commercial decisions, such as the reduction of travel time with 24 hours delivery, the reduction in transport prices offered by the operator, the reliability of the service etc.

The study provides a model of transport logistic distribution based on random parameter logistic model. Usually, this model can be a valuable tool for studying the freight transport demand and possible future developments. With this type of approach on the maximization of the random utility, the phase concerning the construction of the database is fundamental, in our case it consists of a sample of shipments made by Terracciano Group, logistic multimodal operator and market leader.

The construction of the logistic transport model, whether applied to current demand or to the estimate one, must therefore necessarily pass through the phases of specification, calibration and validation, Baumol W.J. and Vinod H.D., (1970**)**. These operations were carried out starting from the information on the behavior of the operator's choice for shipping on the Nola-Milan corridor. A complementary method that can be used concurrently with the disaggregated one is that of the aggregated estimate which uses information such as total demand flows Evers P.T., Harper D.V. and Needham P.M., (1996). The specification phase consists in identifying the mathematical structure of the model, i.e. in the definition of the functional form and of the variables (attributes) that appear in it, which in our case is the random parameter logit model Bayliss B., (1988). This model overcomes the limits of the classic multinomial models but requires a good computational capacity. It allows the insertion of many explanatory variables that have significant weight and that come into play in the repeated choices of our multimodal operator.

Calibration is the most delicate phase of the model and consists in the estimation of the parameters that allow to match the calculated data with the observed one. In the RPM model, some of the coefficients of the utility function variables (time and cost) were obtained in random mode (normal, log normal, triangular, etc) while the others non-random, Friedlander A.F. and Spady R. (1980).

The main behavioral models used for freight distribution demand, routing and vehicles choices, can be:

1. Terminal accessibility with inclusive model
2. Traffic allocation to network by GIS
3. Expert systems and routing optimization.

In our case, it has been applied to a multimodal model operator (logistic operator) with a reduced data base computational system due a lack of information on a new short sea shipping line. The development of this application is certainly an interesting area for RUM model application.

3. Maximum simulated likelihood estimate

The model we used to analyze the modal choice on the Nola - Naples route is a behavioral model with random parameter logit model type (RPLM). These models of random utility, defined by the probability of choosing the alternative j, depend not only on the X_k attributes, on the β parameters, related to the systematic utility also by the θ parameters related to the joint probability distribution function of the ε random residuals.

The estimation method commonly used for disaggregated calibration is thw Maximum Likelihood (ML) that provides the value of the unknown parameters that maximize the probability of an operator of the choices made. If the stratification, on the other hand, is based on the choices made with repeated choices, it is referred to repeated choice-based stratification: for example, in a modal choice model, a sample of the shipments for each transport mode is derived. In this case, the log-likelihood function is given by:

$$\ln L(\beta_1, \beta_2 .. \beta_z ; \theta_1, \theta_1 ... \theta_r) = \sum_{h=1...H} \left(\frac{w_h}{\alpha_h} \right) \sum_{i=1...n_h} \ln p^i [j(i)] \tag{1}$$

where it is:
w_h equal 1
α_h as sampling rate

The tests on the coefficients of the model are based on the reasonableness of the signs of the calibrated coefficients and on their mutual relations. It is a matter of verifying that the coefficients of attributes corresponding to costs or any other disutility are negative, or on the contrary, that the coefficients of attributes expressing utility are positive. Any incorrect signs of the coefficients are an index of errors in the phase of specifying or calibrating the model. The t-Student tests on the individual coefficients verify the null hypothesis (H0) that a coefficient βk is zero and that the βk ML estimate is different from zero for non-sampling errors, through the statistics:

$$t = \frac{\beta_k^{ML}}{Var\left[\beta_k^{ML}\right]^{1/2}} \tag{2}$$

$$P_{ni} = \int \left(\frac{e^{\beta' x_{ni}}}{\sum_j e^{\beta' x_{nj}}} \right) f(\beta) d\beta \tag{3}$$

They also verify that two coefficients βk and βj are equal, using the statistics:

$$t = \frac{\beta_k^{ML} - \beta_j^{ML}}{\left(Var\left[\beta_k^{ML}\right] + Var\left[\beta_j^{ML}\right] - 2\,\mathrm{cov}\left[\beta_j^{ML} \beta_k^{ML}\right] \right)^{1/2}} \tag{4}$$

The χ-square tests on the coefficient vectors, verify the null hypothesis that the vector of the β coefficients is equal to a determined vector β *. For example the null vector, and that the β^{ML} estimate is different from β * only for sample errors, ; this hypothesis is verified through the chi-square statistic which, in the null hypothesis, is asymptotically distributed according to a chi-square variable with a number of degrees of freedom equal to the number of components of β analyzed. The Likelihood Ratio tests on the coefficient vectors are analogous to the previous ones and verify the null hypothesis that the β vector is equal to a β * vector, obtained by imposing a series of constraints on the β vector. The null hypothesis can be verified using the likelihood ratio (LR) statistic:

$$LR(\beta^*) = -2\left[\ln L(\beta^*) - \ln L(\beta^{ML})\right] \tag{5}$$

that, in the hypothesis, nothing is asymptotically distributed according to a variable χ-square with a number of degrees of freedom equal to the constraints imposed in estimating β *. This type of test corresponds to the previous one if the constraints imposed to estimate β * are such as to completely identify the vector, as in the case β * = 0. The tests on the goodness of the juxtaposition of the model (goodness of fit) verify the ability of the model to reproduce the choices made by a sample of subjects through the ρ-square statistic:

$$\rho^2 = 1 - \frac{\ln L(\beta^{ML})}{\ln L(0)} \tag{6}$$

4. Random parameter logistic model (RPLM)

This model can approximate any random utility model and compared to standard logit model does not exhibit IIA property Revelt D. and Train K. (1998). Mixed logit probabilities are the integrals of standard logit probabilities over a density of parameters McFadden D. and Train K. (2000), Train, K. (2003). Functional form a mixed logit model can be expressed in the form:

$$Pni = \int Lni\, \beta f(\beta\, /\emptyset\beta))d\, \beta \tag{7}$$

In the simulation models the utility function is given by $U_{nj} = \beta`_n\, x_{nj} + \varepsilon_{nj}$ with coefficients $\beta`_n$ distributed with density f (β | θ). The parameters in the Mixed Logit models, f (β) generally have continuous distributions, normal, lognormal, uniform, triangular, gamma, etc. Catalani M. and Zamparelli S. (2010). Mixed Logit is a parametric estimation simulation model.
The choice probability is:

$$Lni(\beta) = \frac{e^{\beta'}}{\sum_j^J e^{\beta'}} \tag{8}$$

The probabilities are approximated through simulation for any given value of θ. The average is the simulated probability:

$$\check{P}_{ni} = \frac{1}{R}\sum_{r=1}^{R} L_{ni}(\beta^r), \tag{9}$$

where R is the number of lines.

The simulated probabilities are entered in the loglikelihood function with the following formula

$$SLL = \sum_{n=1}^{N} * \sum_{j=1}^{J} d_{nj}\, ln\, \check{P}_{nj} \tag{10}$$

where $d_{nj} = 1$ if n chose j and zero otherwise. La maximum simulated likelihood estimator (MSLE) is the value of θ that maximizes SLL.

$$L_{ni}(\beta) = \frac{e^{V_{ni}(\beta)}}{\sum_{j=1}^{J} e^{V_{ni}(\beta)}} \tag{11}$$

6. Consignment database

For the calibration of the model, the estimation of the βk parameters of the utility functions with the Greene software of the three modal alternatives: road (1), combined sea-road (2), and rail (3) transport using a Terracciano data base sample with repeated choices. However, it is tested a new maritime experimental line with combined voyage time increasing and on the contrary the transport cost reducing about 50% with eco bonus.

The study focused upon survey carried out on a limited reference sample: this identifies exclusively experimental application without extensive investigation such as the one proposed here, and consequently the result can be understood as indicative to know the dynamics of the market and goods flows.

The functions of random utility with alternative specific variables are as follows:

TT = total transport time
NP = number of pallets
CT = logistic distribution cost
MD = dummy variable = 1 if the goods are perishable, 0 otherwise
MAV = dummy variable = 1 if the goods are of high value, 0 otherwise
Road, Sea comb = specific attributes of the alternatives
A = reliability
S = safety

Calculated the systematic utilities and the probabilities of choice estimated the sum function could be minimized with the generalized least squares method through the aggregated calibration phase.

This makes it possible to use the demand models as analytical tools for the interpretation of the current situation and for the prediction of future scenarios. Furthermore, it is possible to extend the microeconomic concepts of direct and cross elasticity of the demand functions to the models, with respect to infinitesimal variations of the attributes. It should be considered that in application the MD variable was not significant.

7. Results of the application

As already specified the experimental application of two models RPL vs MNL includes a limited extension of the database with only a few maritime consignments of new line. It is necessary to specify that the application based on the NLogit software (Greene W.H. 2002). Table 1and table 2 show the βk coefficient estimate obtained and the related coefficient T. This coefficient allows to verify if an attribute makes a significant contribution to the behavioral interpretation of the model**.**

Table 1: Multinomial logit model.

	Coefficient	*Standard Erro*	*b/St.Er.*	*P[|Z|>z]*
CT	-.00090371	.00126083	-.717	.4735
TT	-.00741378	.00590880	-1.255	.2096
A	.53284795	.16954891	3.143	.0017
MAV	-.51403157	.47542186	-1.081	.2796
S	1.05160779	.22202226	4.736	.0000
A_1	.74942808	.39369800	1.904	.0570
A_2	.52561802	.38308783	1.372	.17
Log likelihood function =	-103.7817			
R-squared =	.22569			
Chi-squared =	48.37261			

Source: Our elaboration

Particularly, Table 2 reports the results of the RPLM vs MNL simulation model as Greene Nlogit code with the first with a major MLS. The random parameters values TT and GT in the utility function derived with normal distribution, reports an acceptable T-statistics with signs as expected and a p(Z)>z in the average. This is a multiplier Lagrange test, give the probability of rejection null hypothesis of the goodness of coefficient, and varies between 0-1.

Table 2: Random Parameters Logit Model (mixed logit) with CT and TT normal distribution

	Coefficient	*Standard Error*	*b/St.Er.*	*P[|Z|>z]*
Random parameters in utility functions				
CT	-.00442309	.00291124	-1.519	.1287
TT	-.04796014	.04364217	-1.099	.2718
Nonrandom parameters in utility functions				
A	.78108968	.35324054	2.211	.0270
MAV	-.63931749	.67535920	-.947	.3438
S	1.24539398	.32792099	3.798	.0001
A_1	.48361700	.63817170	.758	.4486
A_2	.65481500	.61043727	1.073	.2834
Heterogeneity in mean, Parameter: Variable				
CT:NP	.00050939	.00036545	1.394	.1634
TT:NP	.00029664	.00858811	.035	.9724
Derived standard deviations of parameter distributions				
NsCT	.00144604	.00558973	.259	.7959
NsTT	.12839863	.06150715	2.088	.0368
Log likelihood function =	-101.3475			
R- squared =	.24385			
Chi squared =	65.36634			

Source. Our elaboration

The non-random parameter in the utility function as A, S, and Mav have very good T-value a p(Z)>z very low. For ASC (alternative specific constant) variables A1 and A2, parameters are acceptable. As regard, heterogeneity in the mean variables TT and GT to NP have a discrete T- statistics for TT low for GT. As regard, derived standard deviation of parameter distribution Ns CT is very low and good NsGT.
The output of the code evidences a better-generalized log likelihood and R-sqrd for RPL (mixed logit) application model as regard MNL. Both the applications have a low R-sqrd partially due to the size of sample. The direct elasticities are for road transport 0,24, rail 0,08 and for maritime intermodal 0.45, to evidence, for this last, the good reply to changing cost with eco bonus.
In addition, the estimate of the β_k coefficients shows a good level of significance explaining by the T-ratio for MNL. The negative signs of time and cost coefficients are as expected. As regards the calculation of the probability of choice of the vehicle, the model shows a clear prevalence of the probability of choice of road transport equal to 48%, followed by 24% rail transport and a good 28% for combined maritime transport.

8. Conclusions

The experimental application represents a first hypothesis of a logistic distribution model, applied to a real case study, with five variables used. The result in statistical terms of the variables considered suggests expanding sample and confirming the validity and goodness of the model used, also if in presence of a low R-squared.
The model calibration will allow to test in the future scenarios as the impact policies of optimal choice of the transport alternative and strategies from a reduction of transport price and travel time. All those in tune with recommendations of Terracciano Group. The introduction of less polluting vehicles, green and the endowment of electric transport on long distance can be assessed in a targeted maritime mode. Relevant is the advantage for the logistic operator of short sea shipping transport costs reducing (eco bonus) and the significant benefit that this strategy brings to the community.
The new maritime line implementation tested with a reduction transport cost of 50%(eco bonus) led to an increase in traffic of this mode with a reduction in road one with a proportional increase in the probability of choosing. No relevant changing for rail transport.
In short, with the model it is possible quantifying the impact of scenario development, along intermodal corridor due a variation of travel time and transport cost. Interesting will also be to test successively the possibility of using the high-speed rail transport on link Genova- Milano in alternative to road one. All this with a profitable solution both in terms of traffic reduction by road, limiting network decongestion, and create environmental benefits in a congested corridor in Italy.
The Terracciano Group in its strategic planning has already included an upgrade of electric- hybrid vehicles combined with an increase in intermodal railway. These operations represent an important step towards optimization the company's fleet of vehicles, also benefiting from its international image in the transport sector.

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