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Cost, transit time and speed elasticity calculations for the European continental freight transport

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Abstract

The paper presents a set of freight demand elasticities for road, inland waterways and rail transport with respect to a change of total cost of transport, transit time and speed. The calculations are based on origin-destination matrixes and networks made available by ETISPlus, a European transport policy information system. The transportation costs and transit times are computed, for each origin-destination relation, each group of commodities and each transportation mode of interest using a transportation network model. A Box-Cox approach transform the explanatory variables for an aggregated conditional logit analysis. If the estimation and validation steps of the models receive a special attention, the most important added value of this paper is probably the in-depth analysis and interpretation of the estimated parameters, and more specifically the optimal λ values used for the Box-Cox transformations.

Own and cross elasticities are calculated for costs and transit time changes. All these values are computed at the trans-European level, but also for a large region around the Benelux countries, where there is more competition between the three modes. For this region, the impact of the geographical aggregation level of the O-D matrix (NUTS-2 vs NUTS-3) is also examined.

Beside these classical analytical computations, the network model makes it also possible to compute arc elasticities. The obtained values are quasi-identical to the former, but this method allows the computation of 'composite' elasticities, which estimate the impact of a variation of a component present in more than one explanatory variables, such as travel speed, that influences both costs and transit times.

This paper is a follow-up to a general review paper published by Beuthe, Jourquin and Urbain (2014a) in Transport Reviews. In the meantime, a preliminary paper testing the use of the ETIS database and a Box-Cox transformation applied to an univariate utility function (total transport cost) has been published by Jourquin (2019).

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1. Introduction

Elasticities are often used in the context of transport policy decisions for estimating the impacts of changes in the price or cost of transport, but also the impacts of new infrastructure on traffic or on the modal split. The problem is that the studies in the literature present many different values, which result not only from heterogeneous methodologies but also from different databases including specific networks and production localization. This fundamental and widespread problem led, in Europe, to the development of common transport policy databases useful for policy makers, analysts and modelers. The ETIS European framework project (2005) proposed a first implementation of such a database. The following ETISPlus (2012) program further developed this approach to obtain an information system useful for assessing European transport policies: it combines data, analytical modeling with maps and an online interface for accessing the data.

Among other figures, these data provide origin-destination (OD) matrixes for the 10 NST/R "chapters" (groups) of commodities, both at the NUTS-2 and NUTS-3 regional levels[1]. It also provides digitized road, inland waterways (IWW) and railway networks. The files containing these networks must, however, be reshaped as they cannot directly be used for transport assignment.

In order to compute the total cost (*C*) and transit times (T) of transport for each mode, OD pair and group of commodities, the Nodus transportation modeling software is used (Jourquin and Beuthe, 1996; Jourquin, 2005). After a Box-Cox transformation (Box and Cox, 1964), these variables serve as input for an aggregated McFadden conditional logit (McFadden, 1973) modal choice analysis.

Once estimated, the validation of the models proceeds at two different levels, similarly to the approaches discussed by Zhang (2013) and Jourquin (2016):

- From a "node" point of view, for which a comparison of the calculated modal split for each origin-destination pair with the ones found in the ETIS matrixes is performed;
- From a "link" perspective, comparing the calculated flows on the different links of the networks to the flows obtained from the assignment of the each ETIS modal demand matrix on their respective networks.

Actually, the paper separately analyzes two data subsets: the first one covers continental Europe, using NUTS-2 OD matrixes, the second covers a limited region around the Benelux[2] countries ("Benelux+") with more disaggregated NUTS-3 data. On each dataset the conditional logit model is separately estimated for each group of commodities and the corresponding own and cross transport demand elasticities are calculated. As the two data bases differ by their level of aggregation, a comparison of the derived elasticities provides some insight on the impact of the two different geographical granularities.

Next to these values, the transportation modeling permits the calculation of some arc-elasticities. Section 5.4 explains how this alternative method can provide "composite" elasticities, characterized by a simultaneous variation of the two explanatory variables.

This study used only open-access data and cross-platform open-source software. The whole model, including the data preparation steps, runs on Mac OS, Linux and Windows computers.

2. Input data

2.1. Transportation demand and digitized networks

ETISPlus gives public access to several deliverables and many data, among which origin-destination matrices and digitized networks. In the framework of this paper, the OD matrices for the year 2010 are used, both for the NUTS-2

1 The Classification of Territorial Units for Statistics (NUTS = 'Nomenclature des unités territoriales statistiques' in French) is a European geocode standard for referencing the subdivisions of countries for statistical purposes.

2 "Benelux" stands for Belgium, the Netherlands and Luxembourg.

and NUTS-3 regional levels. This dataset is available in CSV format and easy to handle. An OD matrix is available for each of the three transport modes of interest with data for 10 categories of commodities (NST/R chapters 0 to 9). Information about intermodal transport and terminals is not included in these modal matrixes. Therefore, intermodal transport chains cannot be identified, and this type of transport is thus not included in our analysis. The three modal matrixes are merged in order to obtain the total demand, expressed in tons for the year 2010, regardless of the used mode. Henceforth, a modal choice model applied to this merged matrix can provide estimations of each mode demand function and their modal split, which can be assessed by comparison with the original modal matrixes.

The networks are available via a bulk download of ETIS-Netter, in the ESRI shape-file format. Even if the downloaded files can be visualized directly in a GIS software, the networks cannot be directly used for assignments. Some important manipulations are needed to make them “assignment compatible”. Among the main transformation steps, connectors are generated from each centroid to the modal networks whenever some demand or supply exists for a mode in the region the centroid belongs to for at least one group of commodities. A connector links a centroid to the nearest point on the network of the same mode within the NUTS region, or, if no such point exists, to the closed point on the network outside the region. The connectors are of the same mode as the network they connect. As intermodal transport is not explicitly modeled, they are not used to simulate a pre- or post-haulage by truck.

The resulting networks, illustrated by Figure 1, contain 1,177 centroids for the NUTS-2 regions, 2,321 centroids for the NUTS-3 level, 58,687 road links, 1,641 inland waterways (IWW) links and 10,282 railroad links. These networks (and the OD matrixes) actually cover more regions than those analyzed and modelled in this paper:

- The European model (Figure 2) covers the countries belonging to the European Union (EU) or to the European Economic Association (EEA), with the exception of some island countries, like Cyprus, Eire, Malta and United Kingdom, plus some other islands or very peripheral zones within countries.
- The “Benelux+” model (Figure 3) covers the area of Belgium, the Netherlands and G.D. of Luxembourg, plus some NUTS-2 regions in the North of France and Western Germany[3].

These maps also show that the sizes of the NUTS-2 regions are almost homogenous across countries. This is not true for NUTS-3 regions, which are for instance noticeably smaller in Germany than in France. This may introduce some bias in the Benelux+ model.

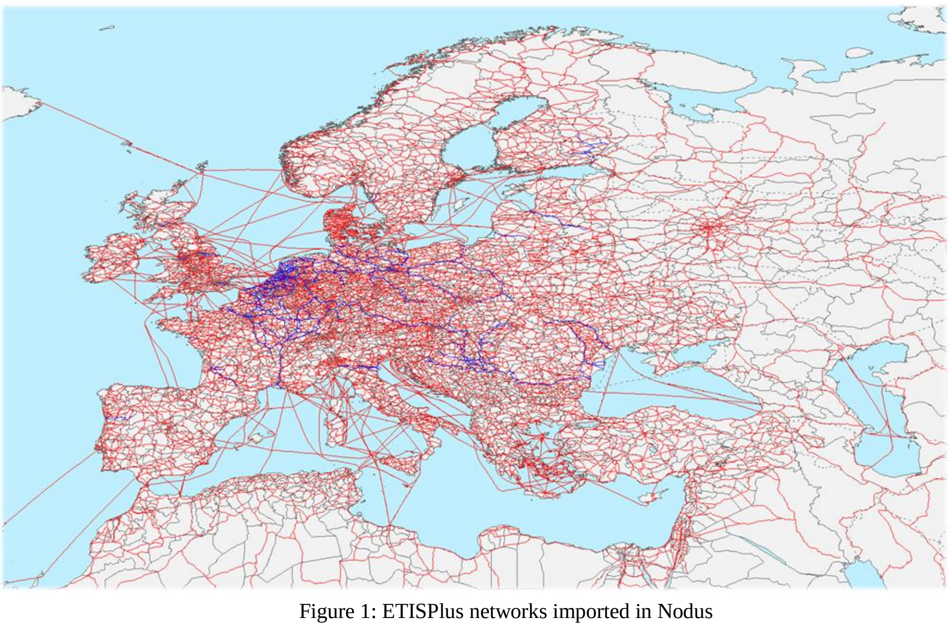

Figure 1: ETISPlus networks imported in Nodus

[3] The exhaustive list of the regions included in both models can be obtained from the authors.

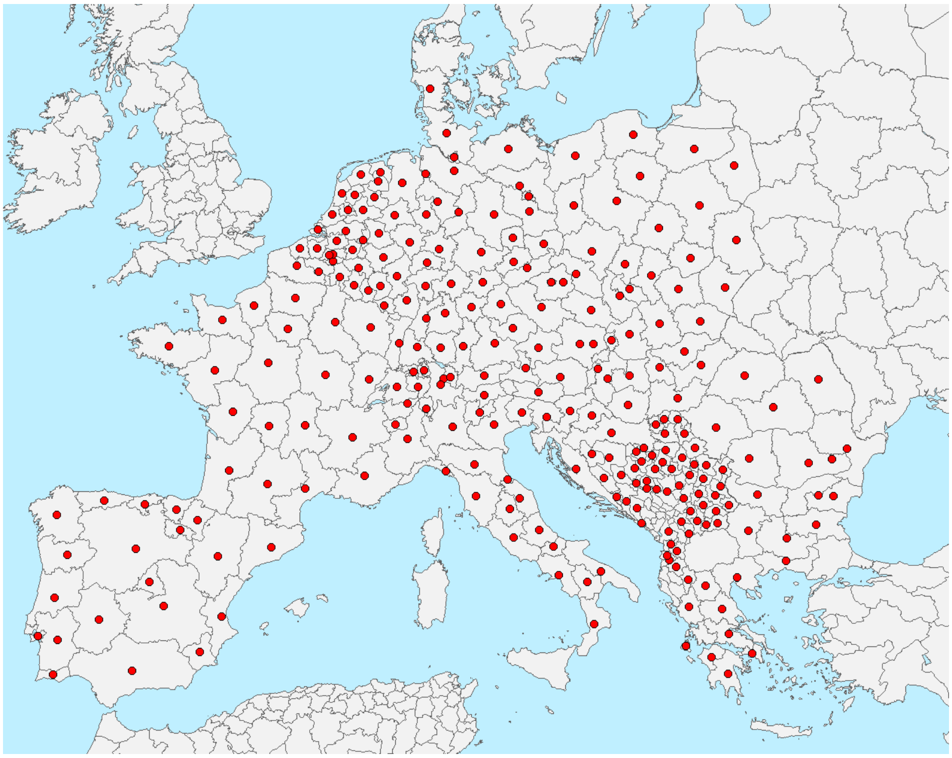

Figure 2: Coverage of the European model (NUTS-2)

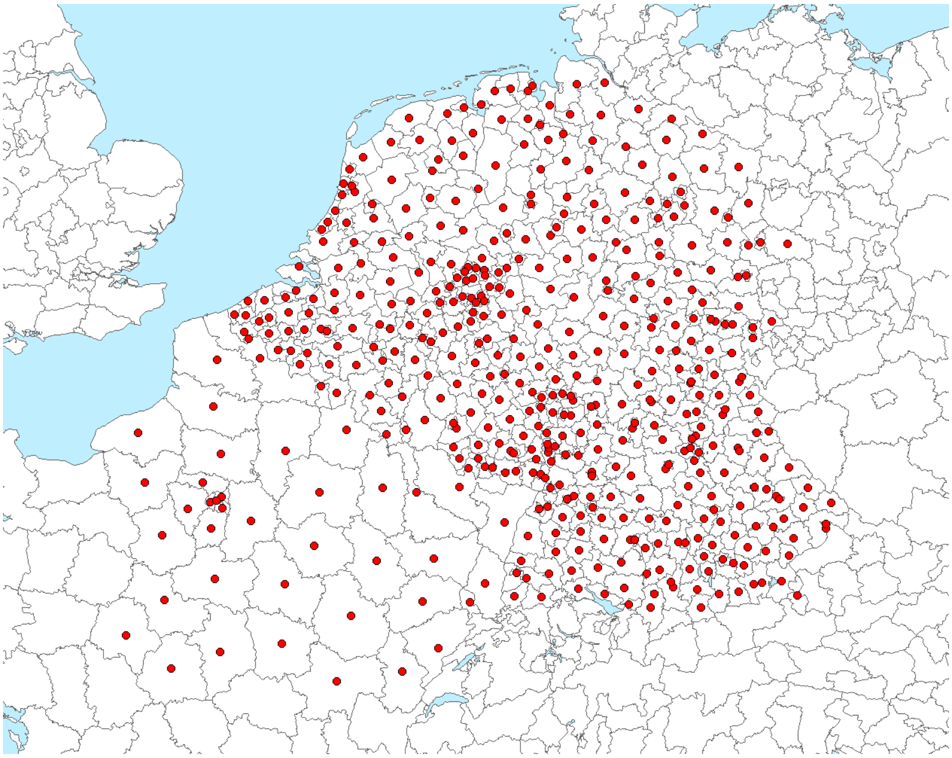

Figure 3: Coverage of the Benelux+ model (NUTS-3)

Table 1 shows that, even if the European model covers a larger region, the demand matrixes for the Benelux+ model contain many more cells, as it contains more disaggregated data.

Table 1: Sizes of the retained demand matrixes

		OD cells with non-zero demand				Market shares (tons)		
Model	Granularity	Road	IWW	Rail	Merged	Road	IWW	Rail
Europe	NUTS-2	339,621	9,406	47,255	346.333	79%	7%	14%
Benelux+	NUTS-3	1,485,290	58,040	178,696	1.582.142	75%	17%	8%

2.2. Total cost functions and transit times

The models developed in this paper use the total cost *C* and the transit time *T* of transport[4] for each mode on each OD relation and for each group of commodities. The cost data is the same as the one used in Beuthe *et al.* (2014a and 2014b).

The most recent release (7.0, http://nodus.uclouvain.be/) of Nodus (Jourquin and Beuthe, 1996) allows retrieving, for each OD pair, each mode and each group of commodities, the loading, unloading, transit and transshipment costs. These costs include those of labor and capital, fuel, maintenance, insurance, etc… as explained in Beuthe *et al.* (2014a). Beside these costs, the total transit times (travel time + loading and unloading durations) are available. Actually, the *C* and *T* values are computed from the results of an assignment of each observed modal OD matrix on its corresponding digitized network. Thus, for each OD relation and each group of commodities, a total cost and a total transit time are obtained for each available mode along with the transported tonnage. When several types of barges can navigate on an OD relation, the one with the cheapest total cost is applied in the modal choice model. In the context of this paper, costs are defined for one type of truck and train, but six types of barges (CEMT classes 2, 3, 4, 5a, 5b and 6). All these barges cannot be used everywhere on the inland waterways network, as their usage is limited by the gage of the rivers.

The loading and unloading costs *ld_cost* and *ul_cost* are fixed costs, though they vary with the mode and the transported goods. Transshipment costs are not defined as intermodal transport is not explicitly modeled (see also the definition used for the connectors in section 2.1). The loading factors are taken from the ECCONET research project presented in Beuthe *et al.* (2014b). They are exogenous but specific for each group of commodities and type of vehicle (truck, train or one of the 6 types of barges). The traveling unit cost, or moving cost, *mv_cost* depends on the length and average commercial speed per mode, as well as on the transported commodity *g*. For a given link *l* belonging to a network of mode *m*, or possibly a type of barge in the case of waterways, it is computed as:

$$mv\_cost_{l,m}^{g} = \frac{Average\ speed_{m}}{Speed_{l,m}} * length_{l} * unit\ mv\_cost_{m}^{g} \qquad (1)$$

As the unit *mv_cost*, expressed in t.km, also contains time-related costs, the *Average speed / Speed* ratio allows for taking into account higher/lower than average costs on slow/fast segments of the network. Indeed, $Average\ Speed_m$ represents the average speed for mode *m* on the total network and $Speed_{l,m}$ is the average speed on link *l*.

The total cost C_m^g of a route between an origin and a destination for a vehicle of type *m* transporting commodities of type *g* is thus equal to:

$$C_{m}^{g} = ld\_cost_{m}^{g} + ul\_cost_{m}^{g} + \sum_{l}^{L} mv\_cost_{l,m}^{g}\ , \qquad (2)$$

where *L* is the set of successive links representing the route.

[4] Only transportation related costs and durations are taken into consideration, ignoring other costs and times that can be encountered along the supply chain, such as warehouse costs for instance.

Similarly, the total transit time has fixed elements (the loading and unloading durations (*ld_duration* and *ul_duration*) and a variable part (the travel duration that depends on the length and allowed speed on the successive links along the route, including the connectors). Thus:

$$T_m^g = ld\_duration_m^g + ul\_duration_m^g + \sum_l^L mv\_duration_{l,m}\ , \qquad (3)$$

$$\text{with } mv\_duration_{l,m} = length_l / speed_{l,m}. \qquad (4)$$

The presence of the length and speed variables in the definitions of *C* and *T* obviously implies that both variables are correlated. This correlation and its level will be discussed below.

3. Modal choice model specification and estimation

Logistic modeling is currently the more common approach for predicting modal choices in transportation economics. Various models of that type are present in the literature, all purporting to handle adequately the available data and problem circumstances. Thus, we should start by considering several important features of the present analysis.

Firstly, the two independent variables, generalized cost and transit time, as well as transport services demand and supply are different for each group of commodities. Hence, it is appropriate to estimate a separate model for each group of commodities. Also, the two variables being specific to each mode, but not to shippers, our analysis applies the McFadden's conditional logit model:

$$Pr_m^g = \frac{\exp(\alpha^g C_m^g + \beta^g T_m^g + \delta_m^g)}{\sum_{j=1}^n \exp(\alpha^g C_j^g + \beta^g T_j^g + \delta_j^g)}, \qquad (5)$$

where Pr_m^g is the probability to choose mode *m* when transporting commodity *g*, and *n* represents the number of modes in the choice set. The conditional logit differs from the multinomial logit as α^g and β^g are not mode specific. However, since the model is solved separately for each group of commodities, these coefficients can vary from group to group. Obviously, we expect that these two coefficients have negative values. Finally, δ_m^g are the calculated intercepts for each mode and group of commodities.

However, the OD matrixes specific to each group of commodities still contain aggregated data: besides cost and time, they contain the average modal choices and the corresponding total annual transport tonnage. Hence, we adopted a weighted logit methodology whereby the transported tonnages weight the mode choice observations in the log-likelihood functions. This procedure does not entirely obviate some possible aggregation biases, but the fact that tonnages are not directly correlated with the two explanatory variables should substantially reduce the problem (Rich *et al.*, 2009).

Table 2: Available infrastructure and usage per mode

		Networks access			Observed usage		
	OD pairs	Road	IWW	Rail	Road	IWW	Rail
Europe NUTS-2	346.333	100%	22%	98%	98%	2%	14%
Benelux+ NUTS-3	1.582.142	100%	51%	98%	94%	3%	11%

Another source of aggregation bias could result from an imperfect or incomplete specification of the transport networks that would not allow a correct assignment of the OD flows. A later section 5.3 comparing results obtained from NUTS 2 and NUTS 3 network specifications will illustrate this problem. On the other hand, the topology of the real networks is such that not all the transportation networks are available everywhere. Indeed, whereas road transport is always an option, railways and inland waterways are not present everywhere. Moreover, even if a mode is available between an origin and a destination, it may not be used. Table 2 illustrates this problem. If access to road and railway networks from/to the centroids (as defined in section 2.1) is almost always possible, this is not the case for the IWW network that only connects 22% of the OD cells at the European level and 51% inside the Benelux+ NUTS-3 regions. The last three columns show that IWW and railway transport are only used in a very limited subset of the demand matrix. In order to resolve this technical problem of a non-existent demand for a mode at some OD, we made the following changes in the dataset:

- The non-existent costs and transit times corresponding to the absence of a modal route between an origin and a destination are replaced by a very high value.
- The null quantities corresponding to the non-usage of a given mode are replaced by a very small value.

Finally, biases can result from an improper specification of the utility function in the logit model. For attenuating this problem, we chose to introduce the usual Box-Cox transformation of the two independent variables, the parameters of which affect the shape of the utility functions from a linear specification to convex or concave forms. Such a transformation appears in equation (6):

$$X_m^{g\,(\lambda_m^g)} = \begin{cases} \dfrac{X_m^{g\,\lambda_X^g} - 1}{\lambda}, if \lambda_X^g \neq 0 \\ \log(X_m^g), if\ \lambda_X^g = 0 \end{cases} \quad (6)$$

The optimal values of the two Box-Cox parameters will then improve the model's maximum likelihood. To some extent, it may also contribute to resolving the problem of collinearity between the two independent variables which may induce biased estimates with, possibly, some unacceptable positive signs. Recently, Gaudry (2016) provided a thorough discussion of the proper methodology to follow for applying this complex approach, explaining that three factors at least should be taken into account when Box-Cox transformations are applied: the maximum likelihood value, the sign and size of the coefficients and their level of significance.

Thus, in the present case, for each group of commodities, for each group of commodities g, a series of λ_C^g and λ_T^gcombinations in the range [-2.4, +2.4] with a step of 0.1 are tested. Combinations are retained that maximize the likelihood of the model while proposing significant estimates with expected signs for the two estimators.

Figure 4 illustrates the importance of looking at the signs of the estimated coefficients in the case of agricultural goods transports (NST/R 0) in the European model. Each curve represents the evolution of the max likelihood for a given value of λ_T^0 when λ_C^0varies from - 2 to 2, and the curve is visible only where the combination of lambda's gives the expected negative signs for both estimators. Only three curves and one isolated point are drawn in order not to clutter the diagram.

- The black square (located on an "invisible" curve) corresponds to the combination of lambda's that maximizes the likelihood. However, as the sign of one of the estimators is wrong, this solution cannot be retained.
- The optimal combination of lambda's is represented by the dot on the plain curve (λ_T^0 = -1) with λ_C^0= 0.4.
- The curve corresponding to λ_T^0= 1 is only visible when $\lambda_C^0$is in the range [-0.8, -0.2] indicating that, for other values, the sign of one of the estimators is wrong.
- The broken curve corresponding to λ_T^0= -0.2 is even more amazing, as expected signs are observed only for values of λ_C^0 in the ranges [-1.2, 0] or ≥ 0.8.

For the case illustrated in Figure 4, C and T are almost perfectly correlated in the road and rail data, while the coefficient of correlation for IWW is equal to 0.87. After transformation of the two variables, the correlations are reduced to 0.79 for road, 0.78 for IWW, while it remains perfectly correlated for rail data. This shows how Box-Cox transformation can help to reduce correlation between the independent variables.

Applying this methodology to our two models, we estimate the α^g, $\beta^g$and δ_m^g coefficients and the value of λ_C^g and λ_T^g using the "mnLogit" R package (Hasan *et al.*, 2016), a faster and parallelized version of the well-known mLogit R package (Croissant, 2013). With 10 groups of commodities and 2 models, 100 coefficients are estimated, along with 20 combinations of lambda values. We present the results in terms of parameters significance levels in Table 3 and the rate of occurrence of lambda values in Table 4.

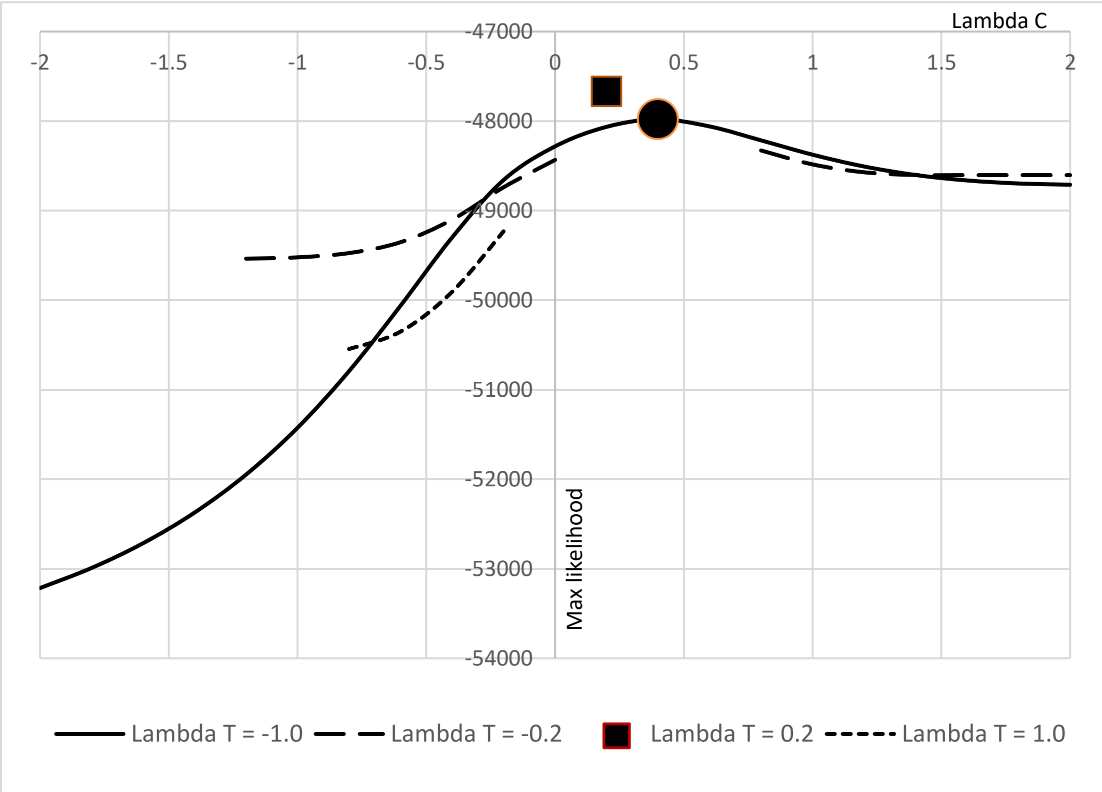

Figure 4: Max likelihood evolution for some lambda's combinations (Europe, NST/R 0)

As shown in Table 3, the t-values of the estimated variables' coefficients[5] are all highly significant except for two cases[6]: β^2 and β^7 for the European model and β^2 for the Benelux+ model. Note that these coefficients appear to be very close to zero, indicating that transit time seems to have little importance in these specific cases. All other 98 coefficients are significant despite the fact that two of the three modes are most often not used (Table 2).

Table 3: Significance of the estimators (t-values)

	Europe NUTS-2					Benelux+ NUTS-3				
Estimator	***	**	*	.		***	**	*	.	
α^g	10	-	-	-	-	10	-	-	-	-
β^g	8	1	-	1	-	10	-	-	-	1
δ^g_{iww}	10	-	-	-	-	10	-	-	-	-
δ^g_{rail}	9	1	-	-	-	10	-	-	-	-
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1										

5 As road is used as reference mode when solving the conditional logit, δ^g_{road} is always set to 1.

6 NST/R 7 corresponds to fertilizers and NST/R 2 to solid mineral fuels.

Finally, Table 4 summarizes the values of the optimal λ^g obtained for the 10 groups of commodities for *C* and *T*. Most values are in the range [-1, 1]. Note that a λ=1 defines a positive linear relation between the variables *X* and $X^{(\lambda)}$. In contrast, $\lambda < 1$ indicates an increasing relation with downward concavity in many cases, meaning that the marginal weight given to the variable is decreasing. Whereas λ >1 indicates an increasing relation with convexity and an increasing marginal weight, which appears to mainly affect the time variable.

Table 4: Occurrences of $\boldsymbol{\lambda^g}$ values per range

	Europe NUTS-2		Benelux+ NUTS-3	
λ^g	*C*	*T*	*C*	*T*
[-2.4, -2[	-	-	-	-
[-2, -1[	-	1	-	2
[-1, 0[	2	1	3	3
[0, +1]	8	3	5	2
]+1, +2]	-	5	1	-
]+2, +2.4]	-	-	1	3

4. Validation of the models

As outlined in the introduction, we performed a two-level validation. Firstly, an analysis of the correlation coefficients *r* between the calculated tonnages and those obtained from the ETIS data for each OD pair, each group of commodities and each mode. Secondly, an analysis of the *r*'s between the model assigned flows on the networks and those derived from the ETIS data for each mode.

4.1. Validation at the OD cells level

The modal choice model provides the tonnage transported by mode *m* between each origin *O* and destination *D* and for each group of commodities *g*. This dataset permits the computation of correlation coefficients between the calculated quantities and those given by the ETIS modal matrixes. The resulting *r*'s appear in Table 5.

Table 5: *r* correlation computed at the OD level

	Europe NUTS-2	Benelux+ NUTS-3
Road	0.947	0.857
IWW	0.688	0.690
Rail	0.854	0.901

Despite the fact that the total cost and transit time are the only explanatory variables, the model seems to perform reasonably well. Its lesser performance for inland waterways transports obviously results from the lack of availability of this mode in many regions, as shown in Table 2.

4.2. Validation at the links level

The validation presented in the previous subsection neglects the role that the network topology can play. As no observed count data is available along the segments of the networks, we used the data of separate assignments for each mode (the observed OD matrix of a mode assigned to its own network) as an approximation of the actual transport operations on each link. These reference flows are then compared to those obtained by a multimodal assignment procedure (Jourquin, 2005), which result is illustrated by Figure 5: the cheapest route is chosen for road and rail transport, whereas, for IWW transport, the route of the cheapest type of barge is chosen, taking into account that this choice depends on the gage of the rivers along the itinerary. The modal shares are computed by a specific modal choice module developed for Nodus, which uses the α_C^g, α_T^g, δ_m^g coefficients and optimal λ_C^g and λ_T^g combinations computed by the econometric model.

Table 6 gives the resulting correlation coefficients between the two sets of flows[7] assigned to the same links. It shows that the results of the modal-split model and of assignments on each mode network are rather similar.

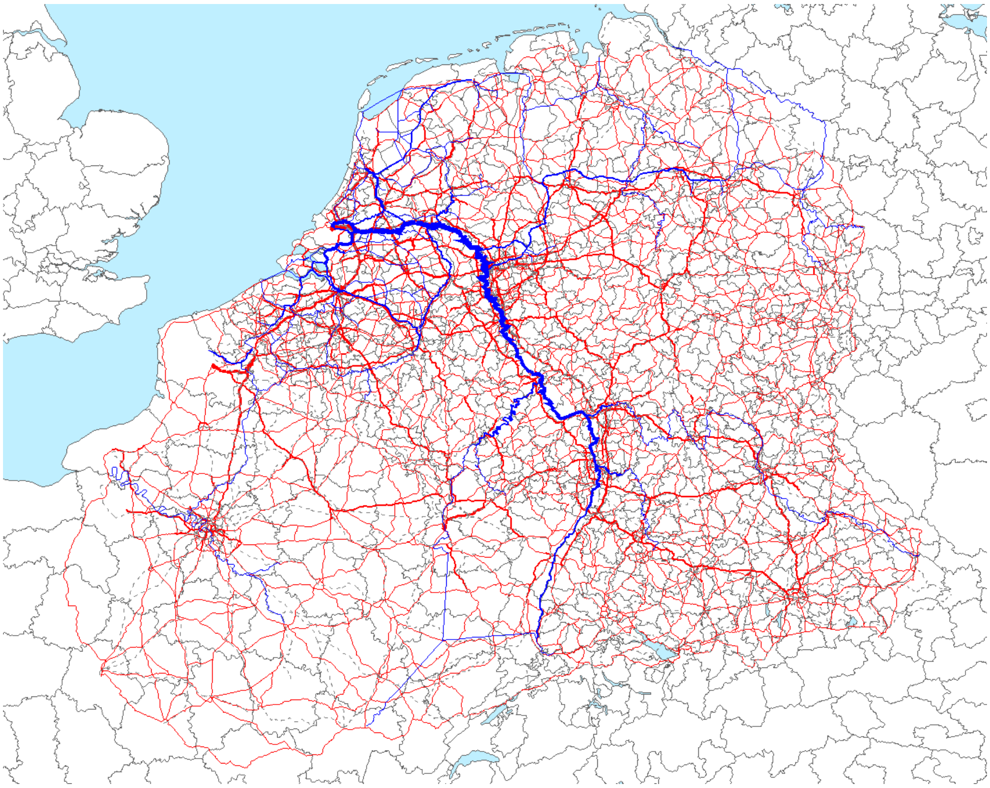

Figure 5: Estimated multimodal assignment of the Benelux+ NUTS-3 model

Table 6 : *r* coefficients computed at the link level

	Europe NUTS-2	Benelux+ NUTS-3
Road	0.974	0.959
IWW	0.886	0.958
Rail	0.880	0.877

5. Calculating elasticities

5.1. Methodology

The values of the standard own and cross elasticities are derived directly from the estimated conditional logit with Box-Cox transformed *C* and *T* as independent variables:

[7] In order not to bias *r*, some links are removed from that calculus: the links connected to only two other links of the same mode, and from which it is not possible to change direction. Indeed, the flow on these links is always equal to the flow on their preceding and following links.

$$Pr_m^g = \frac{\exp(\alpha^g\, C_m^{g\,\lambda_C^g} + \beta^g\, T_m^{g\,\lambda_T^g} + \delta_m^g)}{\sum_{j=1}^{n} \exp(\alpha^g\, C_j^{g\,\lambda_C^g} + \beta^g\, T_j^{g\,\lambda_T^g} + \delta_j^g)} \tag{7}$$

The direct cost elasticity of mode *m* choice probability for group *g* is

$$\frac{\partial Pr_m^g}{\partial C_m^g} . \frac{C_m^g}{Pr_m^g} = \alpha^g C_m^{g\,\lambda_C^g} \, (1 - Pr_m^g) \tag{8}$$

whereas its cross elasticity with respect to the j^{th} mode is:

$$\frac{\partial Pr_m^g}{\partial C_j^g} . \frac{C_j^g}{Pr_m^g} = -\alpha^g C_j^{g\,\lambda_C^g} \, Pr_j^g \tag{9}$$

Obviously, similar formulae are found for the own and cross elasticities with respect to transit time. These formulae define the standard share elasticities. In the context of a discussion of logit modeling, Gaudry (2016) recently strongly recommended the use of a percentage point measure as proposed by Bolduc *et al.* (1989), which expresses the variation of the market share due to a 1% change in the independent variable. This little-known measure can be obtained by multiplying the above equations (8) and (9) by Pr_m^g, so that this probability reference level would not affect the value of the computed elasticity. Considering that the notion of share, or probability, corresponds to a percentage, it can be argued that this measure is a more reasonable estimate of share elasticity in the present modelling context. Indeed, it is the ratio of the percentage variation of the share to the percentage variation of an explanatory variable. In this paper, we will mostly stick to the conventional definition, as it will facilitate comparisons with other results in the literature. Nevertheless, the 'percentage point-elasticity' may reveal itself useful, in some instances, for a better understanding of different elasticity levels between modes or between different studies. In any case, when comparing different values of standard elasticity, one should always keep in mind that a small reference probability, or for that matter a small reference quantity, tends to increase the absolute value of elasticities[8].

5.2. Elasticity estimates

Table 7 summarizes the elasticities for the two independent variables and for each commodity group; they are calculated from the logit models estimated separately over the European NUTS-2 and Benelux+ NUTS-3 databases. The table gives the extreme values (range) and the aggregated figures resulting from a weighted average of the group-specific values. These elasticities relate to the complete set of origins and destinations, including those where choice is restricted to one or two modes.

[8] For help on this issue, let us remind that the elasticity of a theoretical decreasing linear demand function increases (in absolute value) with decreasing demand.

Table 7: Own and cross elasticities on total cost and transit time

		Europe NUTS-2					
Share		Total cost elasticities			Transit time elasticities		
		Road	IWW	Rail	Road	IWW	Rail
79%	Road	-0.09 to -2.56	0.04 to 0.27	0.03 to 1.91	-0.32 to 0.00	0.00 to 0.21	0.00 to 0.31
		-0.29	0.07	0.20	-0.12	-0.08	0.17
7%	IWW	0.59 to 1.86	-0.52 to -2.68	0.03 to 1.53	0.00 to 1.75	-0.01 to -1.94	0.00 to 0.24
		1.07	-1.05	0.24	0.45	-1.07	0.12
14%	Rail	0.63 to 2.05	0.03 to 0.25	-0.83 to -2.25	0.00 to 1.75	0.00 to 0.17	0.01 to -2.15
		1.13	0.12	-1.26	0.44	0.07	-1.05

		Benelux+ NUTS-3					
Share		Total cost elasticities			Transit time elasticities		
		Road	IWW	Rail	Road	IWW	Rail
75%	Road	-0.03 to -1.18	0.00 to 0.26	0.01 to 1.07	0.00 to -0.83	0.00 to 0.45	0.00 to 0.13
		-0.29	0.12	0.12	-0.18	0.14	0.07
17%	IWW	0.14 to 3.65	-0.02 to -3.60	0.02 to 1.30	0.00 to 1.63	0.00 to -1.60	0.00 to 0.14
		1.09	-0.89	0.17	0.82	-0.91	0.08
8%	Rail	0.24 to 3.71	0.01 to 1.32	-0.18 to -4.82	0.00 to 1.92	0.00 to 0.45	0.00 to -2.53
		1.00	0.24	-1.45	0.46	0.13	-0.80

Some high (absolute) values appear in Table 7, like in the case of the – 2.56 own cost elasticity for trucking solid mineral fuels (NST/R 2) in the European model. This high value may partly result from a low share (20%) of road transport for this category of commodities. As explained above, the comparison and interpretation of standard elasticities require some precaution in the context of probabilistic models since these elasticities are not, technically, ratios of proportional variations. Thus, as an example, we can use the actual market shares (Table 2) for transforming the European NUTS 2 average standard cost elasticities for the three modes, respectively -0.29 (road), -1.05 (IWW) and -1.26 (rail), into the percentage point-elasticities –0.22, -0.08, and -0.18. Similarly, the average Benelux+ elasticities, -0.29, -0.89 and -1.45, are transformed into –0.27, -0.03 and -0.16. These lower values look more sensible.

Obviously, it would be interesting to compare the cost elasticities presented in Table 7 with other values found in the literature, since published multimode analyses of freight transport elasticities cover a wide range of values. This diversity of results occurs because of differences in methodologies and available data, and differences between transport markets. We should keep such factors in mind for a fair understanding of calculated elasticities, their appropriate use in further modeling, as well as benchmark references in further studies. The reader will find in Beuthe *et al.* (2014a) a general overview and analysis of many studies striving to estimate transport elasticities in various contexts. Let us only mention here that our present estimates tend to be higher in absolute values than those we obtained in our previous paper and that their value range appears rather broad. The data may partly explain these differences, but the higher level of elasticities is certainly influenced by the different logit modeling: the present model with two Box-Cox transformed independent variables versus a simpler proportional logarithmic model (2014a) with only one variable (total cost), leading to values bound into the [0 - 1] range in absolute value[9].

Table 8 provides detailed information on elasticities for each group of commodities. It also contains the specific estimated lambdas as well as observed modal shares, which allow the reader to transform the standard elasticities into percentage ones. As already indicated in Table 3 almost all coefficients are highly significant. It clearly appears that time-elasticities are substantially weaker than cost-elasticities in both data sets. It is particularly the case for solid fuels

[9] For the corresponding econometric model, the direct elasticity formula would be $\frac{\partial Pr_m^g}{\partial C_m^g} \cdot \frac{C_m^g}{Pr_m^g} = -(1 - Pr_m^g)$.

since their time coefficient is less or not significant at all. The other striking case is the fertilizers in the European data set, which also exhibits a very weak significance. We see that some elasticities are even equal to zero, but that is because we used only two decimals in the tables. In the Benelux+ set, solid fuels obtain zero values for all the direct and cross-elasticities. Actually, this case combines two difficulties: the non-significant time-coefficient, and a not optimal $\lambda_T = 2.4$ because this value came up in computation against the 2.4 upper limit.

Again, the percentage point-elasticities may provide a clearer perception of the effects induced by variations of independent variables. For instance, considering the case of solid fuels in the European model, we can use the actual market shares given in Table 8 for transforming the standard direct cost elasticities for the three modes -2.56, -1.59, and -0.83 into the percentage point-elasticities -0.51, -0.22, and -0.55. Similarly, for the case of iron ore and scraps, the direct cost elasticities -0.32, -2.68 and -2.10 are transformed into -0.27, -0.12 and -0.23. We see that the percentage point-elasticities exhibit a more regular pattern of price effects on demand. Indeed, it appears that the three effects on the solid fuels market are roughly twice as strong as the similar effects on the iron ore and scraps market. More generally, we observe differences between elasticities computed on the European NUTS 2 and Benelux+ NUTS 3 datasets.

Furthermore, we notice, in the first part of Table 8 on the European model, that all lambdas bearing on cost are < 1 and rather small in absolute value, which means that the negative effect is slightly marginally decreasing with cost. This is also the case in the second part of the table on the Benelux+ model, but with two exceptions for agriculture products and minerals & co. In these two cases, the negative effect of cost is progressively increasing, which indicates that many of these goods cannot bear a high transport cost. On the other hand, half of the lambdas bearing upon transport time are > 1 in the European model, meaning that the negative effect of time is marginally increasing with distance. The five concerned groups are metal products, machinery and packed containers, chemicals, fertilizers and solid fuels. Many of these goods are of higher values that require faster delivery to production and distribution chains. In the Benelux+ dataset, only chemicals, machinery and containers, and solid fuels transports show similar effects of transport time within the smaller Benelux+ area.

These differentiated outcomes partly result from different mixes of goods[10] within each group of commodities according to the travelled distance and destination; the higher density of the Benelux+ transport networks also must play a role. Whatever may be the case, these differences send us a warning that elasticities coming out of ‘simple’ econometric models need a careful evaluation considering the many factors that bear upon their estimates. Hence, it is appropriate to underline that, beyond the direct effects of cost and time via their coefficients, the lambda values reflect to some extent the weight that some other logistic factors bear on transport decisions. We could also interpret intercepts’ values in a similar way: indeed, they are not just *ad hoc* adjustment variables, but, actually, express the average relative effects of other missing logistic factors. Since, as it is usual, this model is normalized with a zero value assigned to the road-intercept coefficient, we observe that, in most cases, the estimated rail intercept is smaller than the road-intercept but larger than the IWW-intercept, what corresponds to the dominant position of road in most transport markets with rail coming in second place. There are also a few cases with positive IWW-intercepts, particularly when inland waterway takes a larger share like for petroleum and minerals transports in the Benelux+ area, where the IWW network is widely accessible. Thus, from all these points of view, our results look very coherent. Their diversity according to groups of commodities, like in our previous papers, indicate that one should worry about estimating models and elasticities on the basis of (too) aggregated data.

Beyond these comments on our own work, the present paper limits its scope to themes explored by Rich *et al.* in their two papers (2009 and 2011). They developed an interesting analysis of the data spatial scope and zoning effects on elasticity measures. Indeed, Table 7, interestingly, suggests that these factors could affect our own results since the calculated elasticities are not similar in NUTS-2 and NUTS-3 models. Partial explanations are that the covered areas, the OD matrixes and their geographical dispersion are not identical. Likewise, the transport networks configurations and their accessibility show many differences. Besides these obvious reasons, the aggregation level of the data matrixes may also play a role, a problem to which Rich *et al.* give much attention.

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[10] See Wagner and Lemaitre (2002) for the list of commodities within each group.

Table 8 : Detailed Box-Cox λ values and elasticities per group of commodities

	Europe, NUTS-2			Cost-elasticities			Time-elasticities		
	λ	Mode	Shares	Road	IWW	Rail	Road	IWW	Rail
Agriculture products	$\lambda_C = 0.4$	Road	87.7	-0.18	0.04	0.13	-0.02	0	0
	$\lambda_T = -1.1$	IWW	4.5	1.11	-0.76	0.13	0.17	-0.01	0
		Rail	7.8	1.32	0.03	-1.46	0.17	0	-0.01
Foodstuffs and fodder	$\lambda_C = 0$	Road	93.8	-0.09	0.06	0.03	-0.06	0.02	0.01
	$\lambda_T = -0.2$	IWW	4.5	1.31	-1.34	0.03	0.87	-0.51	0.01
		Rail	1.7	1.47	0.05	-1.53	0.92	0.02	-0.57
Solid fuels	$\lambda_C = 0.2$	Road	20.0	-2.56	0.27	1.91	0	0.01	0.05
	$\lambda_T = 1.3$	IWW	13.7	0.59	-1.59	1.29	0	-0.04	0.03
		Rail	66.3	0.63	0.25	-0.83	0	0.01	-0.02
Petroleum products	$\lambda_C = 0.6$	Road	67.7	-0.63	0.17	0.23	-0.21	0.21	0.14
	$\lambda_T = 0.2$	IWW	22.9	1.01	-0.59	0.10	0.38	-0.68	0.07
		Rail	9.4	2.05	0.16	-1.91	0.62	0.17	-1.17
Iron and scraps	$\lambda_C = -0.2$	Road	84.6	-0.32	0.13	0.26	-0.32	0.09	0.23
	$\lambda_T = 0$	IWW	4.6	1.86	-2.68	0.21	1.75	-1.94	0.19
		Rail	10.9	1.70	0.12	-2.10	1.75	0.09	-1.84
Metal. products	$\lambda_C = 0.4$	Road	78.3	-0.35	0.04	0.35	-0.01	0.02	0.11
	$\lambda_T = 1.2$	IWW	4.4	1.13	-0.91	0.31	0.02	-0.61	0.09
		Rail	17.3	1.27	0.06	-1.61	0.03	0.05	-0.49
Minerals and build. materials	$\lambda_C = 0.5$	Road	79.1	-0.25	0.04	0.14	-0.21	0.15	0.31
	$\lambda_T = 0.3$	IWW	7.5	0.79	-0.52	0.11	0.68	-1.85	0.24
		Rail	13.4	1.02	0.04	-0.89	0.82	0.14	-1.83
Fertilizers	$\lambda_C = -0.1$	Road	34.2	-1.55	0.07	1.60	0	0	0.02
	$\lambda_T = 2.0$	IWW	4.3	0.88	-2.61	1.53	0	-0.05	0.02
		Rail	61.6	0.80	0.14	-1.00	0	0	-0.02
Chemical products	$\lambda_C = 0.2$	Road	80.2	-0.46	0.15	0.27	0	0.03	0.07
	$\lambda_T = 1.8$	IWW	9.5	1.70	-1.51	0.19	0	-0.34	0.05
		Rail	10.3	1.99	0.19	-2.25	0.01	0.08	-0.58
Machinery and containers	$\lambda_C = 0.1$	Road	86.5	-0.18	0.05	0.13	-0.01	0.08	0.20
	$\lambda_T = 1.3$	IWW	5.5	1.01	-0.89	0.09	0.04	-1.43	0.13
		Rail	8.0	1.23	0.06	-1.43	0.10	0.10	-2.15

	Benelux+, NUTS-3			Cost-elasticities			Time elasticities		
	λ	Mode	Shares	Road	IWW	Rail	Road	IWW	Rail
Agriculture products	$\lambda_C = 1.4$	Road	90.5	-0.03	0.004	0.11	-0.18	0.04	0.02
	$\lambda_T = -0.4$	IWW	7.0	0.24	-0.05	0.03	1.63	-0.56	0.04
		Rail	2.5	0.30	0.01	-0.48	1.92	0.05	-0.67
Foodstuffs and fodder	$\lambda_C = -0.1$	Road	91.7	-0.14	0.13	0.02	-0.13	0.05	0.01
	$\lambda_T = -0.3$	IWW	7.1	1.49	-1.74	0.05	1.39	-0.61	0.02
		Rail	1.2	1.75	0.16	-2.02	1.58	0.05	-0.71
Solid fuels	$\lambda_C = 0.1$	Road	17.9	-0.97	0.22	0.68	0	0	0
	$\lambda_T = 2.4$	IWW	23.4	0.15	-0.68	0.59	0	0	0
		Rail	58.6	0.24	0.19	-0.43	0	0	0
Petroleum products	$\lambda_C = 0.8$	Road	59.8	-0.37	0.14	0.03	-0.76	0.45	0.03
	$\lambda_T = -0.2$	IWW	38.4	0.52	-0.22	0.02	1.10	-0.70	0.02
		Rail	4.01.8	1.33	0.15	-1.33	1.71	0.28	-1.23
Iron and scraps	$\lambda_C = 0.1$	Road	88.1	-0.49	0.26	0.18	-0.09	0.05	0.03
	$\lambda_T = 0$	IWW	7.9	3.65	-3.60	0.43	0.65	-0.73	0.08
		Rail	4.0	3.71	1.32	-4.82	0.64	0.26	-0.89
Metal. products	$\lambda_C = -0.4$	Road	78.4	-0.31	0.18	0.15	-0.21	0	0
	$\lambda_T = -1.4$	IWW	7.8	1.15	-2.26	0.25	0.86	-0.02	0
		Rail	13.8	1.12	0.26	-0.98	0.70	0	-0.01
Minerals and build. materials	$\lambda_C = 2.1$	Road	78.2	-0.05	0.002	0.01	-0.40	0.29	0.11
	$\lambda_T = 0$	IWW	15.9	0.14	-0.02	0.02	1.46	-1.60	0.14
		Rail	5.9	0.31	0.01	-0.18	1.38	0.45	-1.83
Fertilizers	$\lambda_C = -0.1$	Road	27.6	-1.18	0.20	1.07	-0.83	0	0.01
	$\lambda_T = -1.5$	IWW	9.1	0.47	-1.90	1.30	0.40	-0.01	0.01
		Rail	63.2	0.45	0.19	-0.66	0.31	0	0
Chemical products	$\lambda_C = 0.4$	Road	79.3	-0.61	0.26	0.21	0	0.05	0.07
	$\lambda_T = 2.2$	IWW	15.4	2.15	-1.49	0.24	0	-0.30	0.07
		Rail	5.3	2.87	0.34	-3.82	0	0.11	-1.16
Machinery and containers	$\lambda_C = 0.6$	Road	85.2	-0.37	0.13	0.23	0	0.12	0.13
	$\lambda_T = 2.3$	IWW	10.0	2.05	-1.20	0.22	0	-1.14	0.13
		Rail	4.8	2.31	0.17	-4.32	0	0.18	-2.53

Many similarities exist between Rich *et al.* work and this paper: both models use a weighted logit with disaggregated demand matrixes per group of commodities and rely on a transport assignment model. Many of their comments on groups' elasticities are similar to ours. Nevertheless, four main differences can be pointed out:

- The geographical scope is very different since Rich *et al.* are mainly concerned by the Oresund region (Denmark and Sweden) problems;
- They pay a special attention to the crossings (by ferry or bridge), using a nested structure for the mode-crossing choice model;
- The transportation modes of interest are different: beside road and railway transport, they introduce maritime shipping, combi-road and combi-rail, but barge transport on IWW is not included;
- No Box-Cox transformation is applied.

Rich *et al.* acknowledge that their elasticities are rather low (in absolute value) and, actually, lower than those found in the literature as shown in Table 9 for the price/cost elasticities[11]. They are also lower than elasticities we previously obtained; and lower than elasticities now obtained with different data and a different modeling (Table 10).

Table 9 : Multi-modes direct price/cost elasticities (cross section)

	Road	IWW	Rail
Levin (1978)	-	-	-0.25 to -0.35
Oum (1979)	-0.41 to -1.07	-	-0.46 to -1.20
Friedlander and Spady (1980)	-0.14 to -1.72	-	-1.45 to -4.01
Friedlander and Spady (1981)	-0.83 to -1.81	-	-0.37 to -1.16
Kim (1987)	-0.10 to -1.24	-	-0.12 to -1.73
Oum (1989)	-0.69	-	-0.60
de Jong (2003)	-0.40 to -1.01	-	-1.40 to -3.87
Rich *et al.* (2011)	-0.01 to -0.13	-	-0.10 to -0.40
Beuthe *et al.* (2014a)	-0.01 to -0.83	-0.39 to -0.99	-0.54 to -1.00

Table 10: Comparison with elasticities from Rich et al. (2009)

	Rich *et al.* (2009)		Own computation (NUTS-3)	
	Cost	Time	Cost	Time
Road	0.00 to -0.13	0.00 to -0.14	-0.03 to -1.18	0.00 to -0.83
Rail	-0.10 to -0.40	-0.08 to -0.42	-0.18 to -4.82	0.00 to -1.83

Their main explanation is that the choice between modes is much restricted in their study as trucking is the only mode available in many zones, so that a change in price or transport quality cannot have a strong impact of the transported volumes, a phenomenon they convincingly identify as a case of structural inelasticity. In our case, the previous Table 2 shows that this problem is somewhat attenuated, as there is practically always competition between two modes in the NUTS-2 as well as in NUTS-3 data (road and rail). Our aggregated direct cost elasticities for the European model, respectively -0.29 (road), -1.05 (IWW) and -1.26 (rail), appear more consistent with what can be found in other references. It is also noticeable that Rich *et al.*'s travel cost and travel time own elasticities are very similar, while our present model produces transit time elasticities that are lower (in absolute value) than cost elasticities.

In their second paper (2011), they also show how they obtain different elasticity levels for different levels of competition between modes throughout Scandinavia. Hence, they warn that aggregation of data may induce bias in

[11] Elasticities given in Table 9 are taken from papers that consider cross-section data and a range of commodities. For more details, see Beuthe *et al.* (2014a).

estimation if it affects the representation of the network and the actual competitive situation between modes. In order to illustrate this problem, we model the same geographical market with two different sets of data. The first one covers the Benelux+ area at the NUTS-2 level, and the second covers the same area at the NUTS-3 level, but without the inner traffic inside each NUTS-2 region. In this way, the geographic area and the total demand are identical for both models. The difference is that the flows between two NUTS-2 regions are distributed among more centroids in the NUTS-3 model, and that the NUTS 3 transport network is denser with more availability of IWW transport solutions.

Table 11: Impact of the geographical aggregation level

		Total cost elasticities					
		NUTS-2			NUTS-3		
Share		Road	IWW	Rail	Road	IWW	Rail
74%	Road	-0.28	0.08	0.12	-0.31	0.21	0.12
18%	IWW	0.80	-0.44	0.15	0.82	-1.01	0.15
8%	Rail	0.87	0.14	-1.33	1.00	0.26	-1.33

Table 11 gives the corresponding elasticities calculated with the same methodology we use in this paper. In the case of road and rail transport, the geographical aggregation level seems to have no real impact on direct and cross cost elasticities. This is an expected result from reading Table 2 (network access), which suggests that the availability rate of these two modes does not play much of a role. In contrast, the availability of waterways is much better at the NUTS-3 level, which explains the higher absolute value of elasticity computed from the NUTS-3 data. This demonstrates the bias that an aggregation of data may produce. In this simulation, the lower cost elasticity results from the reduced density of the IWW network that the aggregation at the NUTS 2 level generated.

5.3. Arc-elasticity calculations

It is also possible compute arc-elasticities with Nodus. Indeed, after estimating a model, the value of an independent variable can be modified (reducing the total costs for a mode by 5% for instance) before running a new modal choice/assignment procedure with the estimated parameters of the corresponding conditional Box-Cox logit model. This two-steps procedure provides the data necessary for computing arc- elasticities using formula (10)[12], in which the Q variable corresponds to transported volumes. Applied to the Benelux+ NUTS-3 dataset, its results appear in Table 12, along with the values published in Table 7 for the same scenario.

$$\varepsilon_{m,j}^{g} = \frac{(Q_{m1}^{g} - Q_{m2}^{g})/Q_{m1}^{g}}{(C_{m1}^{g} - C_{m2}^{g})/C_{m1}^{g}} \tag{10}$$

Table 12: Standard *vs* arc elasticities

	Total cost elasticities for Benelux+ NUTS-3					
	Standard elast. (Table 7)			Arc elasticities (-5%)		
	Road	IWW	Rail	Road	IWW	Rail
Road	-0.28	0.13	0.12	-0.27	0.13	0.12
IWW	1.08	-0.91	0.17	1.07	-0.93	0.18
Rail	0.99	0.24	-1.38	1.01	0.22	-1.40

[12] On the use of various elasticity formulae see for instance T. Litman (2017).

It appears that the values obtained with this method are very comparable to those presented earlier, what validates the method. This opens the way to more flexible elasticity calculations, where several independent variables vary together or where a same component, present in the definition of several independent variables, changes. In the present case, travel speed influences the total cost (Eq. 3) as well as the total transit time (Eq. 4). Indeed, travel speed has an impact on the cost incurred during the displacement of a vehicle (but not the loading and unloading costs) and on the travel time (but not the time needed to load and unload the vehicles). Such ‘composite’ arc elasticities appear in Table 13, assessing the total effect of a speed increased by 5%.

These “composite” elasticities appear slightly lower than the cost elasticities published in Table 7, which is an expected result. Moreover, the difference is smaller in the European model that in the Benelux+ model, because travel speed does not affect the loading and unloading costs. Indeed, the relative weight of these costs in the total cost diminishes with distance.

Table 13: “Composite” arc elasticities on travel speed (+5%)

	Europe NUTS-2			Benelux+ NUTS-3		
	Road	IWW	Rail	Road	IWW	Rail
Road	-0.28	0.08	0.10	-0.29	0.11	0.04
IWW	1.02	-1.01	0.12	1.21	-0.76	0.07
Rail	1.18	0.09	-0.65	1.03	0.16	-0.50

6. Conclusions

The contribution of this paper starts with the implementation of the ETISPlus database into the Nodus multimodal transport network model for freight analysis. This combination provides a good basis for developing comprehensive analyses of freight transport policies and handling comparative work on different econometric methodologies in the field.

The paper then further develops a line of research started with our review paper (Beuthe *et al.*, 2014) on transport elasticity studies, reporting some new results from the application of an aggregated conditional logit model with Box-Cox transforms of two explanatory variables, i.e. total transport cost and total transit time. Two separate sub-networks are defined with different data aggregation levels: the European continental network at the NUTS-2 level and the Benelux+ area with a denser network and OD matrix at the NUTS-3 level. The comparison of these two different sets’ results make it possible to investigate to some extent the problems of bias in aggregation and of structural inelasticity put forward by Rich *et al.* (2009 and 2011).

The main results are:

- A comprehensive discussion about the choice of the lambda to use for Box-Cox transformation. It comes out that these “optimal” lambda’s, and their influence on the shape of the transformed variables, can further be interpreted relatively to the nature of the transported goods.
- A satisfactory estimation of the model applied to the two subsets for 10 different groups of commodities, with validations at the levels of OD cells and traffic on the links.
- Direct and cross standard point-elasticities are computed for each group of commodities. Their values are globally comparable to those published in the literature. However, they are stronger than the figures published in our 2014a paper because of obvious differences in modeling. They are also much stronger than Rich *et al.*’s elasticities, which, they convincingly argue, illustrates a problem of structural inelasticity over the Oresund area.
- Our transit time elasticities are lower than our calculated cost elasticities, whereas they are of equivalent magnitude in Rich *et al.*’s case.
- Beside the values of the lambda’s, the intercepts can also be interpreted. Both reveal, to some extent, the role of ‘qualitative’ factors, *i.e.* other logistic factors beyond direct cost and time variable.
- Percentage point-elasticities are referred to in some cases for comparing elasticities obtained for different goods or from the two data sets. Even if less used in the literature, these are more appropriate in a context of

probability modelling, and they usefully cancel the influence of the reference probabilities' level. Hence, next to the usual standard elasticity values, we give the modal shares for each category of goods, which allow the reader to calculate the percentage point-elasticities in sectors of interest.

- For examining the influence of the geographic aggregation, the Benelux+ network was also set up at the NUTS-2 level. No influence of that different level of aggregation affected the cost elasticities of trucking and rail, since it is not likely that the availability of these two modes is changed. However, the IWW cost elasticity is stronger at the NUTS-3 level, showing the effect of a reduced transport network generated by the data aggregation at the NUTS 2 level. This means that, as far as IWW transport is concerned, the meaning or the use of IWW elasticities computed on the NUTS 2 data may be problematic, at least in some parts of the European space.
- Some arc-elasticities are computed using the results obtained from two network assignments with a small variation on speed, which bear upon both the total cost and time variables. This shows how it is possible to compute "composite" elasticities resulting from simultaneous variations of different variables.

The presented methods, however, suffer from a limitation common to most modal choice models. Indeed, they analyze static data of modal shares so that induced demand is not taken into account. From a more dynamic perspective, this means that our elasticities are probably slightly underestimated. As already pointed out in section 2 (input data), another weakness of the presented models is that they neglect intermodal transport or, more generally, the complexity of transportation chains, that cannot be identified in the used OD matrixes. Finally, the interpretation of the Box-Cox lambda's relatively to the commodities that are transported is limited by the one-digit NST-R level of aggregation. Indeed, some NST-R "chapter" contains goods of very different nature. Using data organized using a two-digits NST-R classification or any other more disaggregated classification could be helpful. This opens the way to new avenues for future research...

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