



Research paper

Direct and cross cost elasticity estimations for freight transport in Europe using constructed dependent variables

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ABSTRACT

Elasticities can be used in the context of transport policy decisions to estimate the impact of changes in transport costs, or the impact of new infrastructure on traffic or modal split, for example. Their estimation is often made difficult by the lack of available data, especially when the study area represents a large international territory.

In this context, a modal choice model with three explanatory variables is presented. In a fairly standard way, transport costs and transit times are used. The originality of the model presented is that it also incorporates two accessibility measures and that the values for the three explanatory variables are computed using origin-destination matrices and digitized networks. Transport costs and transit times are calculated for each origin-destination relationship, type of commodity and transport mode, using a transport network model. The latest also provides the length of each relationship, which is used, along with the annual transported tons, to calculate two accessibility measures.

The article explains why accessibility finds its place in the utility function used in the modal choice model and shows how it improves the model's performance.

The model is further used to compute a set of direct and cross freight demand elasticities for road, inland waterways and rail transport with respect to a change in the total cost of transport on the European territory. The computed elasticities are compared with other values identified in the literature. The presented values can be considered as being credible and robust.

1. Introduction

Elasticities are frequently employed in the realm of transport policy to gauge the effects of altering transport prices or costs, as well as the impacts of introducing new infrastructure on traffic flow and the distribution among transport modes.

When applied to large inter-regional or international areas, modal choice models mostly rely on basic explanatory variables, such as transportation costs or transit times. Other variables, such as the levels of safety, flexibility, frequency, losses during transport or reliability may also play a role in decision-making (Beuthe & Bouffieux, 2008), but the corresponding relevant data is most often not available.

Thorough surveys conducted among shippers, carriers, and receivers also pointed out the significance of network accessibility (Holguín-Veras et al., 2021; Kim et al., 2014; Madaan et al., 2021). Findings from the extensive ECHO (Envois – CHargeurs – Opérateurs de transport¹) survey in France (Guilbault & Soppé, 2009) reveal that over 30 % of shippers prioritize network accessibility when making modal choices. Enhanced

accessibility and connectivity, often facilitated by the development of freight corridors, are recognized as catalysts for economic expansion (ITF, 2022). Indeed, accessibility affects the efficiency, cost, and reliability of transportation. In the context of freight transport, accessibility is important because the timely delivery of goods is critical for businesses to remain competitive. Accessible transport modes provide more options for shippers to choose from, which can result in more competitive pricing and improved delivery times.

Different modes of transportation have different levels of accessibility. For example, road transport is usually the most accessible because it can reach almost any destination with minimal infrastructure requirements. Rail transport, on the other hand, requires dedicated rail lines, which may not be available in certain areas, making it less accessible in some regions.

Accessibility also has implications for environmental sustainability. Indeed, improving the accessibility to more energy-efficient and less emissive freight transport modes can lead to more efficient and sustainable transportation, benefiting both businesses and the society as a

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¹ Shippers - Shippers - Transport operators.

whole.

In a nutshell, transport modes with better accessibility provide shippers with a broader array of choices, potentially leading to more competitive pricing and improved delivery schedules. Hence, it is worth examining the extent to which incorporating accessibility beside transportation costs and transit times in a utility function could enhance the performance of a logit-based modal choice model. This was explored by Jourquin (2023), who presented a proof of concept model, which is further improved in this paper, as the parameters of the accessibility measures are now estimated alongside those of costs and transit times in an integrated model.

Concerning elasticities, a significant challenge arises from the wide array of values reported in the literature, stemming not only from diverse methodologies but also from variations in the used databases, which encompass specific networks and production locations. This prompted the development of shared transport policy databases in Europe, useful for policymakers, analysts, and modelers. The ETIS (European Transport policy Information System) European framework project (2005) was an initial step toward this, while the subsequent ETISPlus initiative (Szimba et al., 2012) expanded upon it, creating an information system for evaluating European transport policies. This system integrates data, analytical modeling, maps, and an online interface for data accessibility. Unfortunately, the database has not been maintained and updated as originally planned.

Among other figures, these data provide origin-destination (OD) matrixes for the 10 NST/R (Nomenclature uniforme des marchandises pour les Statistiques de Transport, Révisée²) “chapters” (groups) of commodities (Table 1) at the NUTS-2 regional levels. It also provides digitized roads, inland waterways (IWW) and railways networks that can, after some reshaping, be used for transport assignments. Using the Nodus transportation modeling software (Jourquin, 2021a; Jourquin & Beuthe, 1996), it is possible to compute the total cost (C), transit times (T) and length (L) of transport for each mode, OD pair and group of commodities. These values can further be used as explanatory variables in a modal choice model, needed to compute demand elasticities.

We are obviously aware that this data set is outdated and that this could lead to several consequences on the estimated elasticities, as these metrics are sensitive to changes in market conditions, consumer behavior, and external factors. As a result, the presented values, used “out of the box”, may conduct poor forecasting or planning decisions. However, the initial goal of this paper is to discuss the impact of the inclusion of accessibility measures in the utility function on the computed elasticities. It is therefore interesting to compare these “new” elasticities to those obtained several years ago using the same dataset.

Table 1
The NST/R groups of commodities.

NST/ R	Description
0	Agricultural products and live animals
1	Foodstuffs and animal fodder
2	Solid mineral fuels
3	Petroleum products
4	Ores and metal waste
5	Metal products
6	Crude and manufactured minerals, building materials
7	Fertilizers
8	Chemicals
9	Machinery, transport equipment, manufactured articles and miscellaneous articles

² Standard goods classification for transport statistics, revised.

2. Spatial accessibility measures

Much has been written about accessibility measures and their ability to evaluate the accessibility impacts of national land-use and transport scenarios, including the related social and economic impacts. It goes beyond the scope of this paper to present an extensive literature review on this topic. The interested reader will find a review in Geurs and Ritsema van Eck (2001) for instance. A more specific review focused on freight transport can also be found in Jourquin (2023).

Accessibility can be defined from a spatial perspective as a measure of the capacity of a location to be reached from different locations (Rodrigue, 2020). Similarly, it can also be defined from an origin node perspective to measure the capacity to reach different destinations.

The General Accessibility Measure (Gutiérrez et al., 1998; Morris et al., 1979; Pooler, 1995) is often applied. It represents the degree of interconnection between a particular reference location and all or a set of other locations in the area (Reggiani et al., 2011; Thomas et al., 2003). The General Accessibility Measure can be defined from a destination (Equation (1)) or an origin (Equation (2)) perspective:

$$A_m^d = \sum_o w_m^o f(L^{od}) \quad (1)$$

$$A_m^o = \sum_d w_m^d f(L^{od}) \quad (2)$$

where:

A_m^d : Capacity of a node d to be reached from other nodes by mode m

A_m^o : Capacity of a node o to reach other nodes by mode m

w_m^d : Weight representing the attractiveness of destination d for mode m

w_m^o : Weight representing the attractiveness of origin o for mode m

L^{od} : Measure of separation (distance, trip length) between o and d

$f(\dots)$: Decay function

The value of these accessibility measures directly depends on the total weights w_m^d (annual tons arriving to destination d by mode m , coming from anywhere, for instance) or w_m^o (annual tons dispatched from o by mode m to anywhere, for instance) and on the trip length L^{od} between the nodes. Most authors use the negative exponential form represented by Equation (3) as a decay function, as it is considered to be closely tied to travel behavior (Handy & Niemeier, 1997; Thomas et al., 2003). However, it appears that the exponential-normal function (Equation (4)) better suits for medium and long-haul freight transport (Jourquin, 2023).

$$\text{Exponential : } f(L^{od}) = e^{-\gamma L^{od}} \quad (3)$$

$$\text{Exponential normal : } f(L^{od}) = e^{-\gamma (L^{od})^2} \quad (4)$$

In these equations, γ is the parameter to estimate.

3. Modal choice model

Logistic modeling is the most common approach for predicting modal choices in transportation economics. Its general form can be written as:

$$P_m = \frac{e^{U_m}}{\sum_{k=1}^M e^{U_k}} \quad (5)$$

where:

P_m : Probability of choosing mode m .

M : Total number of alternative modes.

U_m : Utility of mode m .

U_k : Utility of mode k within the set of M alternatives.

The utility function used in this paper includes the two accessibility

measures presented in Equations (1) and (2). The resulting utility function, with an exponential-normal decay function (Equation (4)), is represented by Equation (6).

$$U_m = \alpha \ln(C_m) + \beta_m \ln(T_m) + (\sigma_m w_m^0 + \tau_m w_m^d) e^{-\gamma(L^{od})^2} + \delta_m \quad (6)$$

where:

C_m = Transportation cost for mode m .

T_m = Transit time for mode m

$\alpha, \beta_m, \sigma_m, \tau_m, \gamma$ and δ_m are the parameters to estimate.

The “accessibility” part of Equation (6) can obviously also be written as in Equation (7):

$$\sigma_m w_m^0 e^{-\gamma(L^{od})^2} + \tau_m w_m^d e^{-\gamma(L^{od})^2} \quad (7)$$

In this formula, the first term of the sum represents the accessibility “to”, as defined by Equation (1): w_m^0 and L^{od} are known, and γ must be estimated, along with σ_m . The same is true for the accessibility “from” (second term of the sum), for which τ_m must be estimated.

The utility function described by Equation (6) is thus an “integrated” formulation that estimates the parameters for the transportation cost, for the transit time, and for the accessibility measures (along with the γ parameter of the decay function) simultaneously.

In this specification, α is not mode specific, as it does not make sense from an economic theory perspective (it would make welfare analysis difficult). For transit times, β_m is mode specific to obtain mode-specific values of time. It is expected that the α and β_m coefficients have a negative sign, as a cost increase or a longer transit time makes a transportation mode less attractive. The parameters σ_m and τ_m should be positive, as better accessibility to/from a centroid is expected to make the location more attractive. Finally, δ_m are the calculated intercepts for each mode. As one mode must be considered as the reference mode (road transport in this paper), δ_{road} is set to 0.

As the OD matrices contain aggregated data of total annual transported volumes for each OD pair, a weighted logit methodology is applied whereby the transported tonnages weight the mode choice observations in the Log-Likelihood functions (Jourquin & Beuthe, 2019; Rich et al., 2009). Instead of simply maximizing the likelihood based on each choice, this procedure multiplies each Log-Likelihood contribution by the weight (annual tons transported). Indeed, without weighing, the model would treat an OD pair moving 1000 tons/year the same as one moving 10,000,000 tons, which would not reflect the economic or operational importance of the OD pairs. The weighted logit ensures that OD pairs with more significant flows have a proportionally larger impact on the estimation.

4. Dataset description

The dataset used in the context of this paper is gathered from the ETISplus European FP7 research program (Szimba et al., 2012). The OD matrices for the year 2010 at the NUTS-2 regional level are used here. They are available for road, railway and inland waterway (IWW) transport, with figures for 10 categories of commodities (NST/R chapters 0 to 9). An in-depth description of this dataset and its implementation into a transportation network model can be found in Jourquin (2017). In the current paper, a subset of the OD matrices is used, focused on pure continental transport. It includes the countries belonging to the European Union (EU) or to the European Economic Association (EEA), apart from some islands and very peripheral zones within countries.

In addition to the OD matrices, digitized networks are available in the ESRI « shapefile » format. Even if the downloaded files can be visualized directly in a GIS software, the ETISplus networks cannot be used for assignments. They are indeed not conceived for this, and some important manipulations are needed to make them “assignment compatible”. The resulting networks contain more than 58,000 road links, 1600 inland waterways (IWW) links and 10,000 railroad links.

This dataset is imported into the Nodus software (<http://nodus.uclouvain.be>) to compute the values of the explanatory variables needed for the modal choice model. Indeed, for each OD relation and each group of commodities, a total cost C , a trip length L , and a total transit time T are obtained for each available mode. A discussion about the way C , T and L are computed can be found in Jourquin (2021b).

5. Estimation of the modal choice model parameters

The parameters of the logit models are estimated using Biogeme (Bierlaire, 2020), an open-source Python package designed for the maximum likelihood estimation of parametric models in general, with a special emphasis on discrete choice models.

Tables 2 and 3 present the values of the estimated parameters. All the estimators have the expected sign. Only α_8 , α_9 and β_{rail4} are not significant at a confidence level of 95 %.

While α_8 , α_9 are not significant, the β parameters for these two groups of commodities (chemicals and manufactured articles/diverse commodities) are highly significant (more than for the other NST/R chapters). This means that, for these two categories of goods, transit time is a more important driver for the modal choice than transportation costs. This is explained by the fact that their average unit value (per ton) is much higher than for other goods. Transport costs, therefore, represent only a small fraction of the value of goods, but it's important not to hold them back too long, if only because of the opportunity costs involved.

All the accessibility estimators (Table 3) have the expected sign and are significant, including the estimator computed for the decay function, indicating that spatial accessibility definitely plays a role in the mode-choice decision. The quality of the network connections to the surrounding areas of the origins and destinations is thus important. This confirms, for instance, that the will of the European Commission to finalize the Trans-European network (TEN/T) makes sense, as this improves accessibility to some regions. However, as the TEN/T network is mainly focused on the most important industrial areas and less on more peripheral regions, national, regional or local authorities should maintain an effort in the development of the local networks to promote the mode of their choice.

Obviously, the model could also, for instance, be applied to a smaller international region, corresponding to a specific TEN/T project, possibly with data with a finer granularity (such as NUTS-3 instead of NUTS-2).

As shown in Table 4, the OD matrixes corresponding to the different categories of commodities are quite different in total demand (transported tons), size (number of OD cells per mode) and geographical spread. The market shares for each mode also considerably vary between categories. Finally, the values of the commodities are also different. This explains why the estimated parameters are quite different from one NST/R group to another.

This diversity also has an impact on γ , the estimated parameter for the decay function. In this context, γ_6 comes out as an outlier. NST/R 6 corresponds to minerals and building materials, such as sand, stones or gravel. These are generally heavy goods with a low market value per ton. They are therefore barely transported over long distances, as the cost of transport is often higher than the value of the goods themselves. For this reason, the corresponding decay function decreases much faster than for other types of goods.

6. Model performance

To assess the added value of adding accessibility measures to the modal choice model, its performance is compared to that of the model with a utility function including only transport costs and transit time (Equation (8)).

$$U_m = \alpha \ln(C_m) + \beta_m \ln(T_m) + \delta_m \quad (8)$$

The log-likelihood and the Akaike information criterion of the model with accessibility are better for all groups of commodities. As these

Table 2
Estimated parameters (part 1).

Estimators		α	β_{road}	β_{iww}	β_{rail}	δ_{iww}	δ_{rail}
NST/R							
0	Value	-0.582	-1.496	-0.482	-7.404	-3.213	24.801
	t-stat	-5.644	-15.565	-4.448	-18.069	-7.332	16.534
1	Value	-1.069	-1.731	-0.734	-9.134	-3.481	28.047
	t-stat	-14.209	-18.708	-6.401	-13.314	-8.053	10.559
2	Value	-0.467	-2.296	-1.951	-16.167	4.303	61.508
	t-stat	-4.088	-22.676	-16.708	-21.804	8.997	21.440
3	Value	-1.849	-2.218	-0.743	-5.529	-2.569	15.971
	t-stat	-13.790	-18.948	-6.369	-8.490	-5.897	6.489
4	Value	-1.559	-2.120	-1.169	-0.433	-1.347	-4.663
	t-stat	-10.496	-13.942	-6.449	-0.389	-1.838	-1.083
5	Value	-0.227	-2.058	-1.369	-9.803	-0.087	34.178
	t-stat	-2.278	-23.759	-13.252	-26.302	-0.215	25.124
6	Value	-0.579	-1.873	-1.242	-6.469	0.901	21.510
	t-stat	-8.703	-28.679	-14.936	-14.782	2.520	12.684
7	Value	-1.070	-1.406	-0.341	-7.922	-4.337	28.388
	t-stat	-10.760	-16.601	-3.148	-14.094	-9.265	13.059
8	Value	-0.112	-2.614	-2.149	-11.562	2.754	39.620
	t-stat	-1.282	-31.214	-25.222	-29.698	9.011	27.631
9	Value	-0.161	-1.867	-2.303	-11.623	3.622	40.831
	t-stat	-1.645	-21.434	-21.743	-26.242	8.939	24.738

Table 3
Estimated parameters (part 2).

Estimators		Accessibility to			Accessibility from			Decay
		σ_{road}	σ_{iww}	σ_{rail}	τ_{road}	τ_{iww}	τ_{rail}	γ
NST/R								
0	Value	0.364	2.302	1.387	0.057	1.135	1.314	-0.064
	t-stat	32.071	43.120	67.830	9.908	30.175	49.768	-4.749
1	Value	0.051	0.540	4.111	0.129	1.050	4.031	-0.031
	t-stat	5.548	60.075	50.526	12.433	41.678	46.269	-2.143
2	Value	1.162	0.814	0.114	0.853	0.215	0.262	-0.545
	t-stat	21.008	20.190	25.014	23.186	14.528	33.988	-5.214
3	Value	0.241	0.187	1.654	0.554	0.534	2.867	-0.665
	t-stat	23.418	49.816	45.021	25.697	39.323	34.424	-14.270
4	Value	0.173	0.098	0.539	0.092	0.068	0.938	-0.543
	t-stat	19.577	14.704	51.949	18.376	10.302	48.076	-5.505
5	Value	0.202	1.918	0.696	0.269	2.192	1.361	-0.429
	t-stat	29.857	48.660	63.435	24.268	51.349	63.828	-11.091
6	Value	0.111	0.407	0.311	0.142	0.258	0.429	-3.419
	t-stat	19.296	44.068	33.172	16.726	35.928	26.528	-11.121
7	Value	1.278	4.946	0.570	0.630	8.703	0.800	-0.299
	t-stat	37.236	43.961	27.998	18.818	28.897	32.088	-10.412
8	Value	0.194	0.554	1.177	0.146	0.611	1.147	-0.080
	t-stat	32.389	69.916	63.897	23.838	65.594	66.487	-6.384
9	Value	0.046	0.182	0.401	0.034	0.189	0.485	-0.022
	t-stat	15.739	68.900	58.978	12.767	69.320	71.535	-2.077

Table 4
Analysis of the OD matrixes.

NST/R	Total demand	OD cells			Market share (%)		
	10 ⁶ tons	Road	IWW	Rail	Road	IWW	Rail
0	420	14586	4741	14519	87.6	4.6	7.8
1	513	15195	5085	15119	93.7	4.6	1.8
2	243	3773	1725	3759	19.4	13.8	66.8
3	284	6138	2356	6096	67.4	23.2	9.4
4	674	6482	2642	6441	84.6	4.6	10.9
5	245	11778	4380	11731	77.9	4.5	17.6
6	1350	12913	4481	12826	79.1	7.5	13.4
7	125	4622	2298	4604	32.9	4.3	62.8
8	378	13608	5106	13571	80.0	9.7	10.4
	1191	25399	6725	25250	86.5	5.5	8.0

performance measures do not give a comprehensive idea of the added value of the accessibility measure in the model, Mean Absolute Percentage Error (MAPE) values are computed. This metric is commonly

used in forecasting. More precisely, the weighted variant of the MAPE (WMAPE) is used (Equation (9)), because a prediction error for an OD relation with an important tonnage is more damageable than for a less significant OD.

$$WMAPE = \sum_{z=1}^Z w_z |A_z - F_z| / \sum_{z=1}^Z w_z |A_z| \quad (9)$$

where:

Z : number of fitted points.

A_z : actual value.

F_z : forecast value.

W_z : weight.

A first series of MAPE values is obtained comparing the contents of the OD cells of the original modal matrices to those of the matrices computed by the modal choice model, the latest being applied to a “merged” matrix, containing the transportation demands embedded in the three original modal matrices. Table 5 shows that the MAPE is

Table 5

MAPE between observed and estimated quantities at the OD level.

NST/R	Model 1 (cost & transit time)			Model 2 (cost, transit time & accessibility)		
	Road	IWW	Rail	Road	IWW	Rail
0	0.19	0.78	0.98	0.12	0.54	0.67
1	0.09	0.91	1.02	0.05	0.58	0.70
2	1.08	0.75	0.33	0.73	0.22	0.18
3	0.40	0.61	0.82	0.23	0.28	0.61
4	0.19	0.94	0.90	0.12	0.69	0.58
5	0.31	1.01	0.87	0.23	0.67	0.66
6	0.26	0.83	0.93	0.19	0.58	0.70
7	0.95	1.02	0.43	0.53	0.48	0.22
8	0.26	0.88	0.93	0.19	0.56	0.76
9	0.20	1.04	1.02	0.12	0.47	0.81

systematically lower for all modes and groups of commodities for the model with accessibility measures, with an average improvement of 14 % for road, 37 % for IWW and 23 % for rail.

Although the values shown in Table 5 reflect the performance of the modal choice model, they do not consider the effect on the estimated traffic within the networks. This can be captured by comparing, for each segment of the network, the observed traffic and the computed one. As no observed count data are available along the segments of the networks, the traffic computed by separate assignments of each mode (the “observed” OD matrix of a mode assigned to its own network) is used as a proxy for the actual transported tonnage on each link T_{link} . These reference tonnages are then compared to the computed $\bar{T}_{link}$ values obtained by an assignment of the computed modal OD matrices.

The figures presented in Table 6 are related to the total traffic on the networks (at least for nonempty vehicles), which is usually of interest to policymakers. They show that the improved model performs better for all modes, especially for IWW. Note that all modes together, the MAPE of the model without accessibility measures is 0.21 while it is reduced to 0.16 when accessibility is included.

7. Elasticity calculations

Using Nodus, it is further possible to obtain the data needed to compute arc-elasticities. Indeed, after estimating a reference scenario in which all the costs are set to their typical level, the value of an explanatory variable (the transportation cost for a mode in this case) can be modified (an increase of 5 % for instance) before running a new modal choice/assignment procedure with unchanged estimated parameters for the logit model. This procedure provides the data necessary for computing arc-elasticities using Equation (10), in which Q corresponds to transported volumes (tons/year). This approach is also very flexible, as it can easily calculate elasticities for all kinds of changes in the explanatory variables of modal choice, including changes in the transport networks.

$$\eta_{m1,m2} = \frac{(Q_{m1}^{1.05C} - Q_{m1}^{1.00C})/Q_{m1}^{1.00C}}{(C_{m2}^{1.05} - C_{m2}^{1.00})/C_{m2}^{1.00}} \quad (10)$$

where:

$\eta_{m1,m2}$: Direct elasticity if $m1 = m2$, cross elasticity otherwise

$Q_{m1}^{1.00C}$: Quantity transported at reference cost by mode $m1$

$Q_{m1}^{1.05C}$: Quantity transported by mode $m1$ when cost is increased by 5 %

Table 6

MAPE between “observed” and computed traffic on the networks (proxy).

Model 1 (cost & transit time)			Model 2 (cost, transit time & accessibility)		
Road	IWW	Rail	Road	IWW	Rail
0.14	0.91	0.49	0.11	0.44	0.44

$C_{m2}^{1.00}$: Reference cost for mode $m2$

$C_{m2}^{1.05}$: Increased cost (by 5 %) for mode $m2$

Obviously, with a cost increase of 5 %, the denominator is always equal to 0,05.

The complete procedure can be summarized as follows.

- 1) The dataset is used to estimate the parameters of the weighted logit/utility function (Equation (6)).
- 2) A user-specific modal choice plugin was developed for Nodus, that uses the estimated parameters (Tables 2 and 3) and applies the modal choice model on a per-OD basis during the assignment step (Nodus combines modal-choice and assignment in a single step).
- 3) An initial assignment of the OD matrices is carried out using the reference costs. For each OD pair, an annual tonnage is estimated for each applicable transport mode. Consequently, the weight of each observation (i.e., each OD pair) varies according to the demand (tonnage), and the modal share of each mode also differs from pair to pair. This process allows for the computation of the total tonnage yearly transported by each mode.
- 4) A second assignment of the OD matrixes is performed with modified costs (a 5 % increase in the costs of road transport for instance). As in the previous step, tons per mode are obtained for each OD pair and a grand total per mode can be computed.
- 5) These aggregate totals are then used to calculate arc elasticities (Equation (10)). While their discussion applies to individual observation, our approach is comparable to the weighting procedure proposed by Hensher and Greene (Hensher & Greene, 2016), as the influence of the marginal impact of extreme values is minimized in the elasticity computation, since the numerator reflects the difference in total tonnage between the two assignments, effectively dampening the effect of outliers.

As explained by Hensher and Greene, this weighting procedure can, however, create the illusion that the IIA (Independence of Irrelevant Alternatives) property of the logit model has been relaxed. Specifically, the cross-elasticity is no longer identical across all alternatives. This effect is, in fact, solely due to the weighting procedure. This phenomenon can be observed in the values published in Table 7.

As it is well known that the computed values of arc elasticities can vary considerably depending on the magnitude of the change in the variable under study, a sensitivity analysis is conducted using scenarios with cost increases of 10 % and 25 %. The full set of elasticities is presented in Appendix 1 and Appendix 2, while a comparison of the aggregated elasticities can be found in Table 8. It appears that values remain fairly stable from one scenario to the next.

8. Comparison with other elasticities published in the literature

It is interesting to benchmark the cost elasticities published in Table 7 with those reported in other studies, given the wide spectrum of values documented in the literature on freight transport elasticities. Dissimilarities exist because of methodological disparities, variations in available data, and distinctions across transport markets. It's crucial to consider these factors to grasp the calculated elasticities accurately, and to appropriately utilize them in further modeling. For a comprehensive examination of numerous studies attempting to estimate transport elasticities across different contexts, readers can refer to Beuthe et al. (2014). Among all the references cited by these authors, those with a comparable context (data types and methodologies) to the one presented in this paper are listed in Table 9.

The calculation of elasticities for freight transport is fairly recent. Indeed, it's only since the end of the 1970s that complete specific articles on the subject have been published. Thereafter, interest in the subject seems to have waned, as we have to wait several years to find new publications. A third wave of research was identified from the very late

Table 7
Computed direct and cross cost elasticities.

NST/R	Road (1) elasticities			IWW (2) elasticities			Rail (3) elasticities		
	$\eta_{1,1}$	$\eta_{1,2}$	$\eta_{1,3}$	$\eta_{2,1}$	$\eta_{2,2}$	$\eta_{2,3}$	$\eta_{3,1}$	$\eta_{3,2}$	$\eta_{3,3}$
0	-0.05	0.01	0.03	0.38	-0.39	0.02	0.37	0.01	-0.37
1	-0.05	0.03	0.02	0.68	-0.67	0.01	0.82	0.02	-0.81
2	-0.27	0.03	0.25	0.05	-0.12	0.07	0.10	0.02	-0.12
3	-0.30	0.16	0.14	0.45	-0.50	0.05	1.03	0.13	-1.12
4	-0.13	0.03	0.10	1.01	-1.18	0.22	0.81	0.06	-0.85
5	-0.04	0.01	0.03	0.10	-0.14	0.04	0.12	0.01	-0.13
6	-0.09	0.03	0.06	0.30	-0.34	0.05	0.36	0.02	-0.38
7	-0.40	0.03	0.37	0.25	-0.46	0.21	0.24	0.02	-0.26
8	-0.01	0.01	0.01	0.05	-0.05	0.00	0.07	0.00	-0.07
9	-0.01	0.00	0.01	0.03	-0.03	0.00	0.10	0.00	-0.10
Aggregate	-0.08	0.02	0.05	0.28	-0.32	0.05	0.30	0.02	-0.32
Max	-0.40	0.16	0.37	1.01	-1.18	0.22	1.03	0.13	-1.12
Min	-0.01	0.00	0.01	0.03	-0.03	0.00	0.07	0.00	-0.07

Table 8
Sensitivity analysis of the aggregated arc-elasticities to different changes in costs.

Costs +5 %			Costs +10 %			Costs +25 %					
	Road	IWW	Rail		Road	IWW	Rail		Road	IWW	Rail
Road	-0,08	0,02	0,05	Road	-0,07	0,02	0,05	Road	-0,07	0,02	0,04
IWW	0,28	-0,32	0,05	IWW	0,28	-0,31	0,04	IWW	0,27	-0,28	0,04
Rail	0,30	0,02	-0,32	Rail	0,30	0,02	-0,31	Rail	0,29	0,02	-0,29

Table 9
Published direct price/cost elasticities computed using a comparable context.

	Road	IWW	Rail
Levin (1978)	–	–	-0.25 to -0.35
Oum (1979)	-0.41 to -1.07	–	-0.46 to -1.20
Friedlaender and Spady (1980)	-0.14 to -1.72	–	-1.45 to -4.01
Friedlaender 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
Beuthe et al. (2001)	-0.06 to -4.42	0.00 to -3.61	-0.04 to -10.5
De Jong (2003)	-0.40 to -1.01	–	-1.40 to -3.87
Rich et al., 2009	-0.01 to -0.13	–	-0.10 to -0.40
Beuthe et al., 2014	-0.01 to -0.83	-0.39 to -0.99	-0.54 to -1.00
Jourquin and Beuthe (2019)	-0.09 to -2.56	-0.52 to -2.68	-0.83 to -2.25
This paper	-0.01 to -0.40	-0.03 to -1.18	-0.07 to -1.12

1990s until 2010. Thereafter, it was mainly Beuthe and Jourquin who pursued similar systematic work. Note that it is essentially their figures published in 2001 that remain cited, while they explain in their 2014 paper that the values published in 2001 are overestimated (in absolute terms) due to the estimation method they used. To the best of our knowledge, the most recent publications in which freight transport elasticities are presented are focused on specific cases, such as transport corridors for instance (Kurtulus & Çetin, 2020; Tjandra et al., 2024).

The models whose references are listed in Table 9 are all based on aggregated cross-section demand data, such as that used for this paper. Most of them also apply a (multinomial) logit model.

Note that elasticities have also been computed using aggregated time series or disaggregated data. The interested reader can find an extensive review of this literature in Beuthe et al. (2014).

Among the references cited in Table 9, two publications have a very close background to what is presented in the current paper.

Indeed, many similarities exist between the work of Rich et al. (2009) and this research: both models use a weighted logit with disaggregated demand matrixes per group of commodities and rely on a transport assignment model. Nevertheless, three main differences can be pointed out.

- The geographical scope is very different, since their work is mainly concerned by the Oresund region (Denmark and Sweden).
- They pay special attention to the crossings (by ferry or bridge), using a nested structure for the mode-choice model.
- The transportation modes of interest are different: beside road and railway transport, they introduce maritime shipping, combi-road and combi-rail, but IWW transport is not included.

Also note that they 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.

The other paper of interest is the one written by Jourquin and Beuthe (2019), as the authors used the same database (ETISPlus OD matrixes at NUTS 2 level) and the same digitized networks and transportation model. The two main differences are that.

- They used a bivariate utility function (transportation cost and transit time) in a “pure” conditional logit model (both α and β are mode specific).
- The explanatory variables are Box-Cox transformed.

The novelty of the elasticities presented in this paper is that they are computed using a utility function that includes accessibility measures (Equation (6)).

As shown in Table 10, the elasticities obtained with the method presented in this paper are lower (in absolute values) than those presented in the paper of 2019. This is obviously because the utility function presented here includes additional explanatory variables proven to be relevant (Table 3). Indeed, the various metrics mentioned earlier (t-stat, signs of the estimators, log-likelihood, Akaike criterion, MAPE) all show that the improved model is more robust. The accessibility-related

Table 10
Elasticities published in Jourquin and Beuthe (2019) vs those of this paper.

	η Road		η IWW		η Rail	
	Tr. Policy 2019	This paper	Tr. Policy 2019	This paper	Tr. Policy 2019	This paper
Road	−0.09 to −2.56	−0.01 to −0.40	0.59 to 1.86	0.03 to 1.01	0.63 to 2.05	0.07 to 1.03
	−0.29	−0.08	1.07	0.28	1.13	0.30
IWW	0.04 to 0.27	0.00 to 0.16	−0.52 to −2.68	−0.03 to −1.18	0.03 to 0.25	0.00 to 0.13
	0.07	0.02	−1.05	−0.32	0.12	0.02
Rail	0.03 to 1.91	0.05 to 0.37	0.03 to 1.53	0.00 to 0.22	−0.83 to −2.25	−0.07 to −1.12
	0.20	0.05	0.24	0.05	−1.26	−0.32

independent variables account for part of the explanatory power of modal choice that was previously attributed exclusively to transport cost and transit time. Consequently, the model incorporating accessibility is expected to be less sensitive to changes in transport cost, resulting in lower elasticities (in absolute terms).

Some of the estimated elasticities may still appear relatively high in absolute terms. This can be attributed to the structure of the data and the scope of the case study, which covers most European countries. At this continental scale, not all transport modes are available for every origin–destination pair. While road transport can typically link any two points, rail infrastructure is less widespread, and inland waterways are even more limited in availability. Consequently, the option to choose between transport modes exists only for certain market segments. Within these segments, competition among modes is stronger, making rail and inland waterway transport more sensitive to cost changes. This also explains their overall low market shares. Obviously, in regions where these modes are more developed, such as the Benelux countries and the Rhine corridor, their market shares are significantly higher, with inland waterways in some cases even surpassing rail.

9. Conclusion

Accurate elasticity estimates are crucial for transport infrastructure project analysis as they measure (freight) demand sensitivity to changes in factors like fuel prices, transit times, or tolls. They help forecast the impact of freight flows, cost savings, economic benefits, toll revenues and environmental effects such as emissions reductions, bearing in mind that poor estimates can distort demand forecasts, leading to inflated/deflated usage, revenue and benefit projections.

This paper further develops a line of research started with a review paper by Beuthe et al. (2014) and developed in Jourquin and Beuthe (2019), adding a third computed explanatory variable into the utility function used in the modal choice model. Indeed, three data can be obtained by calculation in a transport model, i.e., the cost of transport between each origin and destination, its total duration (transit time) and the length of the trip. Cost and transit time are recognized in the literature as important explanatory variables in modal choice and can thus be used directly. This is not the case for the trip length. This data is therefore used here, along with the transported volumes embedded in the origin–destination matrices, to calculate two accessibility measures, which prove to be relevant independent variables.

Network accessibility is indeed crucial for freight transport mode choice, as it impacts efficiency, cost, and reliability. Well-connected networks reduce travel time, lower transportation costs, and enhance delivery reliability, making certain modes more appealing. Additionally,

good accessibility expands market reach, enabling businesses to serve more locations competitively. Overall, strong network connections enhance the feasibility and attractiveness of various transport modes, driving better logistics and economic outcomes.

The case study that is described adopts an international European perspective, making it relevant for major European initiatives such as the Trans-European Transport Network (TEN-T), but the model could be applied to smaller regions, possibly using finer-grained data (e.g., NUTS-3).

To evaluate the impact of incorporating accessibility measures into the modal choice model, two sets of Mean Absolute Percentage Errors (MAPE) are computed. A first set compares the observed and model-estimated tonnages for two modal choice models (with and without the accessibility measures). It comes out that the model with accessibility measures consistently yields significantly lower MAPE values. Secondly, a comparison between transported tonnage along the segments of the digitized transportation networks is conducted. Again, the model integrating the accessibility measures outperforms the other. By improving the predictive capacity of transport network models without overcomplicating the econometric framework, the enriched modal choice model offers a clear advantage.

The model is further used to compute direct and cross elasticities. After having challenged the robustness of the method used, the obtained values are compared with other figures found in the literature, computed using a comparable methodological approach or dataset.

The computed elasticities exhibit lower absolute values compared to those documented in Jourquin and Beuthe (2019), which were computed using the same databases. The differences result from the incorporation of additional explanatory variables in the utility function that capture some of the explanatory power previously attributed solely to transport cost and transit time. Consequently, the model demonstrates reduced sensitivity to fluctuations in transport costs, leading to lower elasticities in absolute terms. However, the presented elasticities also remain somewhat higher than those found in Rich et al. (2009), which methodological framework (but not the data) is also close to the one used in Jourquin and Beuthe (2019). The authors acknowledge, however, that the values they obtain are too low for a number of reasons. Therefore, the elasticities published in this paper can be considered as credible and robust.

It should be noted, however, that the dataset used is somewhat outdated. It was used anyway to be able to compare the obtained elasticities with those presented in the literature, calculated using the same data. Caution should therefore be exercised when utilizing the figures published here for forecasting or planning purposes, as the model would obviously benefit from being applied to more recent data.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to improve the readability of some paragraphs during the revision process. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix 1. Arc elasticities computed with a 10 % cost increase

NST/R	Road (1) elasticities			IWW (2) elasticities			Rail (3) elasticities		
	$\eta_{1,1}$	$\eta_{1,2}$	$\eta_{1,3}$	$\eta_{2,1}$	$\eta_{2,2}$	$\eta_{2,3}$	$\eta_{3,1}$	$\eta_{3,2}$	$\eta_{3,3}$
0	-0.04	0.01	0.03	0.37	-0.38	0.02	0.36	0.01	-0.36
1	-0.05	0.03	0.01	0.68	-0.65	0.01	0.82	0.02	-0.78
2	-0.26	0.03	0.24	0.05	-0.12	0.07	0.10	0.02	-0.12
3	-0.30	0.15	0.13	0.45	-0.49	0.05	1.02	0.13	-1.08
4	-0.13	0.03	0.09	1.00	-1.12	0.21	0.80	0.06	-0.81
5	-0.03	0.01	0.03	0.09	-0.13	0.04	0.12	0.01	-0.13
6	-0.09	0.03	0.06	0.29	-0.33	0.04	0.36	0.02	-0.37
7	-0.39	0.03	0.36	0.24	-0.44	0.21	0.23	0.02	-0.25
8	-0.01	0.01	0.01	0.04	-0.05	0.00	0.07	0.00	-0.07
9	-0.01	0.00	0.01	0.03	-0.03	0.00	0.10	0.00	-0.10
Aggregate	-0.07	0.02	0.05	0.28	-0.31	0.04	0.30	0.02	-0.31
Max	-0.39	0.15	0.36	1.00	-1.12	0.21	1.02	0.13	-1.08
Min	-0.01	0.00	0.01	0.03	-0.03	0.00	0.07	0.00	-0.07

Appendix 2. Arc elasticities computed with a 25 % cost increase

NST/R	Road (1) elasticities			IWW (2) elasticities			Rail (3) elasticities		
	$\eta_{1,1}$	$\eta_{1,2}$	$\eta_{1,3}$	$\eta_{2,1}$	$\eta_{2,2}$	$\eta_{2,3}$	$\eta_{3,1}$	$\eta_{3,2}$	$\eta_{3,3}$
0	-0.04	0.01	0.03	0.36	-0.35	0.02	0.34	0.01	-0.33
1	-0.05	0.03	0.01	0.65	-0.59	0.01	0.80	0.01	-0.70
2	-0.25	0.03	0.23	0.05	-0.11	0.06	0.09	0.02	-0.11
3	-0.28	0.14	0.12	0.42	-0.45	0.04	0.99	0.12	-0.95
4	-0.13	0.03	0.08	0.98	-0.99	0.19	0.78	0.05	-0.73
5	-0.03	0.01	0.03	0.09	-0.12	0.04	0.11	0.01	-0.12
6	-0.08	0.02	0.05	0.28	-0.31	0.04	0.34	0.02	-0.34
7	-0.37	0.03	0.34	0.22	-0.40	0.19	0.22	0.02	-0.23
8	-0.01	0.01	0.01	0.04	-0.05	0.00	0.06	0.00	-0.06
9	-0.01	0.00	0.01	0.03	-0.03	0.00	0.09	0.00	-0.09
Aggregate	-0.07	0.02	0.04	0.27	-0.28	0.04	0.29	0.02	-0.29
Max	-0.37	0.14	0.34	0.98	-0.99	0.19	0.99	0.12	-0.95
Min	-0.01	0.00	0.01	0.03	-0.03	0.00	0.06	0.00	-0.06

Data availability

Data will be made available on request.

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