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Martin Koning, François Combes, Raphael Piendl, Gernot Liedtke

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DOSSIER

Pratiques logistiques et enjeux du transport de marchandises : une comparaison franco-allemande.

Logistics practices and freight transport challenges: a French-German comparison

Transferability of models for logistics behaviors: A cross-country comparison between France and Germany for shipment size choice

La transférabilité des modèles de comportements logistiques :
Une comparaison France-Allemagne pour le choix de la taille des envois

Martin KONING, François COMBES, Raphael PIENDL, Gernot LIEDTKE

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Abstract Transferability is seen as one important rationale for justifying the application of behavioral transport demand models. Concerning freight transportation, behavioral models of shipment size choice gain more and more attention by modelers because of two reasons: First, shipment size models could explain a major proportion of heterogeneity caused by the multitude of actors and shipments; secondly, they link firms' behaviors to their logistics activities. However, the transferability of prevalent shipment size choice models is complicated due to different functional approaches used in econometric estimates and due to the varying occurrence of different variables in the underlying surveys. This clearly limits the applicability of the models for other case studies with related contexts.

Martin KONING (✉)
Université Paris-Est, AME, SPOTT, IFSTTAR,
F-77447 Marne-la-Vallée - France
courriel : martin.koning@ifsttar.fr

François COMBES (✉)
Université Paris-Est, AME, SPOTT, IFSTTAR,
F-77447 Marne-la-Vallée - France
courriel : francois.combes@ifsttar.fr

Raphael PIENDL (✉)
German Aerospace Center (DLR), Institute for Transport
Research,
Rutherfordstr. 2, 12489 Berlin, - Germany
Courriel : Raphael.Piendl@dlr.de

Gernot LIEDTKE (✉)
German Aerospace Center (DLR), Institute for Transport
Research,
Rutherfordstr. 2, 12489 Berlin - Germany
courriel : Gernot.Liedtke@dlr.de

In this article, the transferability of continuous shipment size choice models is investigated by applying the same functional approach to a dataset from France and an equivalent dataset for Germany. In this way, we check the robustness of this approach in regard to different logistics variables and we analyze potential similarities in logistics behavior. Starting with an analytical model for shipment size choice, a descriptive analysis follows which compares for both countries the central figures related to shipment size choice. Afterwards, elasticities gathered from the estimated models are checked against each other and the transferability issue is empirically questioned. Finally, possible reasons for differences in behavior, probably caused by differences in transport cost or in inventory cost, are discussed. It turns out, that the flow of goods exchanged between a shipper and its client explains a major proportion of heterogeneity in France and in Germany, and that the impact of this variable is very similar. Furthermore, differences in the storage costs approximated by the value density are obtained. Logistics variables have similar impacts; they can, however, be neglected in a strategical forecast model. Concluding, for the example France and Germany, the behavior models could be transferred.

Keywords: Freight modelling, transferability, shipment size, France, Germany.

Résumé La transférabilité constitue une des principales justifications en faveur des modèles visant à prévoir la demande de transport. En ce qui concerne le fret, les modèles comportementaux abordant la taille des envois de marchandises sont de plus en plus étudiés, et ce pour deux raisons. Ces modèles permettent tout d'abord de prendre en compte une grande part de l'hétérogénéité caractérisant les acteurs économiques et les marchandises envoyées. Par ailleurs, ces modèles

permettent de relier les comportements des chargeurs à leurs pratiques logistiques. Il est toutefois notable que la transférabilité de ces modèles est complexifiée par la multitude des spécifications économétriques utilisées ou encore par la variété des variables récoltées dans les différentes enquêtes.

Cet article questionne la transférabilité des modèles de tailles d'envois en appliquant la même méthodologie à deux bases de données comparables, l'une pour la France et l'autre pour l'Allemagne. Ce faisant, nous étudions la cohérence de cette modélisation et nous analysons les similitudes dans les comportements logistiques des chargeurs. Après avoir présenté notre modèle analytique, nous décrivons les données. Nous comparons alors les élasticités estimées pour la France et l'Allemagne et nous questionnons la transférabilité des résultats. Par ailleurs, nous discutons les origines des divergences observées, en liens notamment avec les coûts de transports ou les « coûts d'inventaire ». Le flux total de marchandises expédiées entre un chargeur et son client explique une grande part de la taille des envois en France et en Allemagne, avec un impact similaire de cette variable dans les deux pays. Par ailleurs, nous observons un effet différencié des coûts de stockage, approximés par la densité de valeur des marchandises. Si les variables logistiques semblent avoir un impact similaire sur la taille des envois, elles ne sont pas stratégiques pour un modèle de prévision. Au final, cet exercice illustre le potentiel de transférabilité des modèles comportementaux analysant le transport de marchandises, dans le cas de l'Allemagne et de la France tout du moins.

Mots-clés : modélisation du fret, transférabilité, taille d'envois, France, Allemagne.

1. Introduction

It is reasonable to state that research in transportation sciences is characterized by an asymmetry between studies on passengers' mobility and freight, the latter being somehow under-looked as compared to the major importance of goods' movements within the global economic system¹. Be that as it may, research in freight transport produced over the years various theoretical constructs [1], often confirmed by numerical applications, aimed at identifying and understanding the rationales behind the choices of multiple actors involved in these operations.

There are many types of models in freight transport research [2, 3, 4, 1, 5]. Behavioral models² are an important category, given the nature of data generally available regarding freight transport. In contrast to passenger transport, large scale surveys of shippers and/or receivers are scarce – due to privacy protection issues, due to the cost for acquiring complex data of firms, and finally due to the sometimes underestimated importance of freight in infrastructures policy and planning. Against this background, researchers generally use particular datasets in order to deduce elasticities via behavioral models, and then introduce these elasticities in fully-fledged spatialized models calibrated with aggregate transport data. Ideally, these behavioral models are estimated with directly relevant data; however such data might not be readily available. This raises the question of models transferability (see [6, 7, 8, 9] to what extent is it possible to transfer elasticities estimated on data gathered in one specific context to another context?

When it comes to the transfer of behavior models, it is important to connect behavior to structural data and – if possible – to inherent characteristics of the members of a given population. In freight transport, two important characteristics of a shipper are its economic sector and its firm's size (measured either in turnover or workforce). However, these two variables are not enough to capture completely the heterogeneity of shippers' behaviors. Moreover, there isn't any comprehensive establishment survey linking shipping behavior to firms' sector and size.

A direction to better understand the heterogeneity of behavior of apparently similar shippers is to introduce additional variables. One such variable is the flows of goods between shippers and receivers. Indeed, this variable is closely related to the choice of shipment size – the decisions how to partition the annual flow of goods exchanged between two individual firms into individual shipments. It captures a large share of heterogeneity of shippers' behaviors, and it constitutes a link between intralogistics, storage processes and vehicle movements.

The theoretical considerations of shipment size choice initially date back to [10] who calculated the optimal batch size in a production context, where a producer has to balance machine set-up costs against inventory costs. The solution of this optimization problem is called the "Economic Order Quantity" (EOQ), and it can be readily

¹ To question this intuition, we have used the search tool proposed on the Sciencedirect web-site (last accessed 10th of February 2017). Searching in journals focused on Economics, Business, Engineering, Energy and Environmental sciences, we have found 18,843 titles, keywords or abstracts referring to "passenger" or "mobility" (over 2000-2017). The same search with the words "freight" or "logistics" gave us 4,066 results.

² According to [2], disaggregate freight transport models are separated into two different typologies: behavioral models, which deal with the utility maximization process of physical distribution managers and inventory based models, which attempt to model the decision process of an inventory manager. In general, these designations are rather for classification purposes than describing the specifics of the models ([3]). Indeed, inventory based models are as well based on behavioral considerations e.g. the microeconomic behavior of a firm by minimizing its total logistics costs. Thus, when it is dealt with behavior and behavioral models in this article, the authors do not refer to the definition of [2] and address instead any freight transport demand model dealing with behavioral considerations of specific actors.

applied to a freight transport context. The problem is then to determine the optimal shipment size, as a trade-off between transport costs (smaller shipments are more expensive to transport per ton) and inventory costs (larger shipments cause more stock of inventory). [11] analytically enhanced the model with mode choice considerations forming the idea of a “total logistics cost” function, applied to a shipper-receiver relationship. The total logistics cost function can be seen as the freight transports’ counterpart of the “generalized cost” used in passenger transport. These authors showed theoretically how important it is to introduce this decision-making process to understand mode choice and vehicle choice.

In order to address this specific logistics behavior empirically, various approaches exist in the literature (see the reviews by [12] or [13]). First, shipment size decisions are either treated independently of/conditioned on other decisions [13, 14, 15]. Second, they can be modeled jointly with mode choice [16, 17, 18], transport chain choice [19, 20] or vehicle type choice [21, 22]. Further, analyses may be distinguished by the treatment of the shipment size variable. Beside the handling of shipment sizes in a categorical fashion based on the findings of [23], who states that certain shipment size categories can be delimited due to given vehicle and bundle sizes [13, 16, 18, 19], the modeling of shipment size choice is also treated continuously by using shipment sizes observed in the data [24, 14, 22, 21]. Moreover, rather inductive approaches using plenty of explanatory variables [16, 18, 19, 21] can be contrasted with more deductive approaches based on a microeconomic behavioral model and that minimize the before-mentioned total logistics costs function [13, 22, 20, 17]. In particular, [14] empirically validated the appropriateness of the EOQ model conditioned on mode choice enabling the application of shipment size choice for an entire population of heterogeneous firms. This appropriateness is constituted by the low amount of key strategic variables, the microeconomic behavioral basis and the high explanatory power of the key variables, e.g. the strength of the shipper-receiver relationship notably.³ These findings therefore provide a potential starting point for further investigations of behavior-sensitive shipment size choice modeling, such as the potentials of transferability for a continuous and independent road transport shipment size model.

This article presents a simple econometric exercise contrasting the results of the EOQ model in the cases of

France and Germany, using sound and comparable identification strategies as well as empirical materials. Our contributions to the literature are the followings:

First, we are clearly focused on the transferability of logistics behavioral models. With that respect, this research is closely related to the work by [9] who propose a transferability analysis of “freight trips generation” behaviors. Despite a remarkable volume of articles dealing with shipment size choice modeling approaches, as noted above, we are not aware of any previous attempt that investigates and compares in the same research the shipment size’s determinants for two distinct countries. Such knowledge seems necessary to transpose accurately the results found in specific conditions to other case studies. Obviously, conducting this kind of empirical exercise must deal with challenges inherent to data access and comparability, because we want to be sure that information is understood and measured in the same manner in two different places, or at two different dates. Fortunately, the surveys on road freight operations on which are based our econometric estimates allow us conducting robust comparative analyses.

Second, it seems of interest to test the EOQ model for the two biggest countries in Europe. Taken jointly, France and Germany thus accounted in 2013 for 29% of the population in the 28-EU, 37% of its GDP and - more specifically for our research purpose - 35% of total tonnages moved on roads in Europe (statistics from Eurostat).⁴ Even if these countries do not present the same economic structures and specializations, one can reasonably postulate that France and Germany share together more similarities than they do with their surrounding neighbors. As a consequence, it appears relevant to investigate whether this apparent likeness is confirmed on the specific topic of the freight shipment size.⁵

The rest of this article proceeds as follows: Section 2 presents the theoretical EOQ model that enables one to identify the structural determinants of the chosen shipment size. The French and German databases used to test this model empirically are then described in Section 3 whereas Section 4 is focused on the econometric results. In addition of contrasting the estimates found for the two countries, both qualitatively and quantitatively, we propose some statistical tests to question the shipment size model transferability. Because some shipment size’s determinants differ across

³ In most shipment size models, alternatives are typically characterized by per ton-kilometer costs, travel times, reliabilities, etc. The underlying assumptions are that costs do not depend on the shipper-receiver commodity flow. This is most often due to the fact that even in disaggregate datasets, there is no information about the shipper-receiver relationship, and thus no possibility to introduce this information in the model. But shipment size and mode choices do not depend on the characteristics of the shipper alone; they depend heavily on the characteristics of the shipper-receiver relationship, hence the effectiveness of models where this relationship is accounted for.

⁴ For the tonnages: http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=road_go_ta_tott&lang=fr. The 35% figure is found by considering the 25-EU.

⁵ Given the strength of commercial relationships between France and Germany, our results may be informative to construct one shipment size model useful to assess French-German trade.

countries, a tentative discussion on the sources of this heterogeneity is presented in Section 5. Section 6 concludes and calls for further research.

2. Modeling framework

The EOQ model stipulates that a firm i sends a regular flow of commodities Q_i (expressed in tonnage) to its client, localized at distance d_i from its factory unit. Since freight operations are discrete, these commodities are moved as shipments. The shipper is assumed to select the shipment size s_i (also expressed in tons) that minimizes a total logistical cost function (TLC_i) which accounts for its own logistical costs, including transport costs, and for the logistical costs of the receiver, as far as the reception and warehousing of the commodities are concerned.

Formally, the TLC is calculated for a given time period (say a year), and for the shipper-receiver pair. It consists of three components:

$$TLC_i = C_i^I + C_i^{II} + C_i^{III} \quad (1).$$

The first component is the fixed per-shipment cost C_i^I . It depends on o_i , the order cost supported by the shipper each time a shipment is prepared, dispatched and received, as well as on the share of the transport cost which does not depend on shipment size. Some of these costs (expressed in euros/shipment) account for the resources necessary to realize the transaction (administrative costs for instance) as well as for the preparation and the processing of the commands, or for fixed cost of immobilizing vehicles during loading/unloading. They do not depend directly on the shipment size, but rather on the shipment frequency Q_i/s_i :

$$C_i^I = \frac{o_i Q_i}{s_i} \quad (2).$$

The second component of TLC_i , C_i^{II} , consists of two parts: first, the variable per-shipment transport cost, which is assumed to be proportional to the commodity flow Q_i and to the traveled distance d_i , up to the unit transport cost tc_i (in euros/ton*kilometer); second, on the capital opportunity cost linked to the so-called “inventory in transit”, a function of the interest rate⁶ (r), the travel time (tt_i) and the value density of the shipped goods (v_i , in euros/ton/hour). These costs depend on the annual flow of commodities linking the shipper to its client Q_i . They do not depend on shipment size:

$$C_i^{II} = Q_i(tc_i d_i + rtt_i v_i) \quad (3).$$

The third component of TLC_i is the origin inventory cost C_i^{III} . It encompasses the warehousing (w_i) and capital cost (rv_i) “on the inventory” at the origin and destination. It is proportional to the average amount of commodities in the origin and destination warehouses at any time ($s_i/2$ at the origin and also at the destination, for a total of s_i). For the sake of simplicity, we here assume that the stock replenishments are instantaneous (no “stock-outs”):⁷

$$C_i^{III} = s_i(w_i + rv_i) \quad (4).$$

All in all, the TLC can be rewritten as:

$$TLC_i = \frac{o_i Q_i}{s_i} + Q_i(tc_i d_i + rtt_i v_i) + s_i(w_i + rv_i) \quad (5).$$

As made clear, TLC_i is convex in s_i . Its differential with respect to s_i is:

$$\frac{\partial TLC_i}{\partial s_i} = -\frac{o_i Q_i}{s_i^2} + (w_i + rv_i) \quad (6).$$

The value of s_i that minimizes TLC_i is:

$$s_i^* = \sqrt{\frac{o_i Q_i}{(w_i + rv_i)}} \quad (7).$$

Put differently, the optimal shipment size s_i^* increases with the total commodity flow Q_i exchanged between the shipper and its client and the shipment size-independent fixed cost o_i . By contrast, s_i^* decreases with the storage and capital cost ($w_i + rv_i$) linked to the inventory. As a consequence, there is a trade-off between these three dimensions when deciding which quantity of goods must be sent. It should be noted that the optimal shipment size depends on transport cost only through the shipment size-independent cost component. This does not mean that the shipment size-dependent cost component is not important: in particular, mode choice depends strongly on both components (see e.g. [17] on the generalization of EOQ to mode choice).

From an econometric point of view, this structural model of shipment size choice can be estimated through Ordinary-Least-Squares (OLS) techniques by using the log-transformation of variables shown in equation (7) and by adding an error term (ε_i), assumed i.i.d. with mean zero and constant variance:

⁶ The interest rate for a given shipper depends on the shipper’s financial structure and other factors. See the discussion in Section 5. The implicit assumptions underlying this specification is that first, shippers are willing to pay for faster transport; second, that this willingness to pay is linearly related to the value density of the products. While this hypothesis can seem quite strong, it is consistent with empirical evidence in [14].

⁷ In addition, we ignore potential costs linked to safety stocks at the shipper’s or client’s places or those arisen from goods’ deterioration during the transport operation (“iceberg” costs). Our specification is simpler than the general specification in [11].

$$\ln(s_i^*) = \alpha + \beta \ln(Q_i) + \emptyset \ln(w_i + rv_i) + \varepsilon_i \quad (8),$$

where we expect that $\beta = 1/2 = -\emptyset$ and $\alpha = 1/2 \ln(o_i)$ because fixed cost is hardly observable.

The basic EOQ model can be extended in, at least, two ways. First, some authors [25, 26, 22] have shown, either theoretically or empirically, that the distances-dependent transport cost tc_i may be inversely related to the shipment size. This is due to the use of larger vehicles for big shipments and savings on fuel/time costs with heavier vehicles, used for long distances. Such relationship between the traveled distance and the shipment size may also be linked to the risks of unreliable deliveries, proportional to the kilometers driven and to the weight of the shipments. Modeling this effect with an affine function into equation (8), it can be assumed that the traveled distance d_i impacts positively the optimal shipment size s_i^* [22].

Second, the constant term α can be decomposed with available information on the idiosyncratic characteristics or logistical requirements of the shipped goods. Such process may be relevant to approximate some of the unobserved fixed cost o_i , but also other (non structural) determinants of s_i^* . Actually, monitoring, administrative or communication costs between the economic actors involved with a given transaction may be higher in the case of international shipments. Moreover, the resources devoted to the preparation and the conditioning of temperature-controlled shipments are probably quite different than those necessary for standard cargo. To put this heterogeneity of freight operations in perspective, our “extended” model additionally includes a vector X_i controlling for some of the shipments’ characteristics⁸, so that:

$$\ln(s_i^*) = \alpha + \beta \ln(Q_i) + \emptyset \ln(w_i + rv_i) + \gamma \ln(d_i) + \mu X_i + \varepsilon_i \quad (9).$$

We now present the empirical material used to test this simple model in the cases of France and Germany. In particular, Section 4 will contrast the signs, the sizes and the significance of the parameters estimated for each country. We will also question the relevancy of transferring results found in France, for instance, to the German case in order to predict the size of shipments sent in latter country, and vice-versa.

3. Data

As stressed in the Introduction, a major challenge when trying to estimate the EOQ model in a cross-country perspective relates to data access and information comparability. Thus only a few surveys on freight operations contain the main explanatory variables of the optimal shipment size, as shown in equations (8) and (9). These surveys are generally referred to as “Commodity Flow Surveys” (CFS). Few large scale CFS exist around the world; the French ECHO survey [27, 28], the US CFS [29], the Swedish one [30], and the Japanese one, presented broadly in [31] or in [32]. The report by [33] presents and compares these databases. Obviously, one must be confident in the equivalent meaning of the different questions collected during different surveys. Fortunately, we enjoy in this research comparable information for France and Germany, even if the years under study differ. Importantly, we here focus only on road freight operations. In addition of reducing the heterogeneity in the observed shipped goods, freight moved on roads accounts for the large majority (more than 65-80%) of tonnages moved in both countries.⁹

French information comes from the ECHO survey, collected in 2004 and 2005 [27, 28]. This dataset describes a total of 10,462 shipments executed by about 3,000 establishments¹⁰ representative of the French economic system (aside from raw material and services to households or firms). The ECHO survey includes four different waves of questions which focus, respectively, on the characteristics of the shipper and of the receiver and on their mutual relationship, on the shipment itself, and on the transport operations, and on all the economic agents involved in the transport operation (including freight forwarders). The fact that the ECHO survey provides information on the shipper-receiver relationship makes it a critical asset for empirical shipment size modelling, as the shipper-receiver commodity flow rate is an essential explanatory variable of shipment size. For instance, the US and Swedish CFSs quoted above do not provide this information. As a consequence, the ECHO survey is probably one of the deepest freight databases in the world. It is worth noting, however, the fact that only road freight transport observations are analyzed in this paper, and the occurrence of missing values, results in 3,486 useable observations.¹¹

The German dataset was gathered early 2013 in the frame of a federal research project on the “Calculation of freight traffic modal shifting” (see details in [13]). The

⁸ From an econometric point of view, the vector X_i is additionally useful to moderate potential “omitted variable biases”, i.e. when a given variable (unobserved by the modeler) affects simultaneously the dependant variable and one (or more) of its determinants. In the case of drought for instance, both the value density of agricultural products and the shipment size may be affected by extreme climatic events.

⁹ http://ec.europa.eu/eurostat/tgm/table.do?tab=table&init=1&language=fr&pcode=t2020_rk320&plugin=1

¹⁰ The INSEE (French National Institute of Statistics and Economic Studies) defines an establishment as “a production unit that is geographically individual but legally dependent on an [firm]” and a firm as “the smallest combination of legal units that is an organizational unit producing goods and services, enjoying a certain decision-making autonomy, especially for the allocation of its current resources”.

¹¹ We have removed from the ECHO dataset all shipments below 30 kilograms because they describe parcels rather than freight.

observations were ascertained via computer-assisted personal interviews with the logistics employees of 474 companies covering all areas of raw material, manufacturing and wholesale sectors. The chosen firms have been randomly drawn from an extensive business-directory of 10,000 addresses. During each interview, two freight operations - and their corresponding

attributes - were recorded. Due to many missing values and the emphasis put on road transport, the final dataset is restricted to 487 shipments. Even if using the same number of observations for both countries would have been preferable, we believe the size of the German sample to be satisfactory enough to draw robust conclusions on that basis.

Table 1. Summary statistics

Country	France (2004-2005)		Germany (2013)	
<i>Statistics</i>	<i>Mean</i>	<i>Std. Dev.</i>	<i>Mean</i>	<i>Std. Dev.</i>
Shipment size (tons)	5.99	8.71	13.47	9.75
Annual flow (tons)	1,783.78	9,478.71	1,845.45	2,369.29
Value density (euros/ton)	14,381.89	96,453.95	11,311.84	55,958.44
Distance (km)	266.26	272.90	447.81	363.40
International shipment (%)	12.7	33.2	14.0	34.7
Food (%)	27.83	44.82	11.91	32.42
Bulk (%)	16.95	37.53	8.21	27.49
Pallets (%)	54.88	49.77	43.74	49.66
Dangerous (%)	3.33	17.94	12.73	33.37
Temperature-controlled (%)	9.93	29.90	9.86	29.84
Fragile (%)	11.10	31.42	15.61	36.33
Voluminous (%)	5.77	23.31	30.80	46.21
Observations	3,486		487	

Sources: Authors' calculations from ECHO and from the German datasets.

Table 1 provides comparative summary statistics. Looking first at the main variable of interest, the shipment size, we see that French carriers send shipments that are twice less heavier than their German counterparts: 6 tons in France vs. 13.5 tons in Germany. One explanation might be given by the sampling strategy of the German survey which focused on long haulage distance transports with shipment sizes above one ton. Even if the varying levels of the theoretical shipment size's determinants probably explain some of the difference (see equation (7) and below), the sectoral ownership of the German asked firms (raw material, manufacturing and wholesale) could also be influential here. Contrasting the standard deviations and the mean values, more heterogeneity in shipment sizes is found within the French sample.

The two main explanatory variables of the standard EOQ model are the annual flow of commodities for a given shipper-client pair and the inventory costs linked to goods' storage and immobilization. Whereas the first information is fully available, we unfortunately lack knowledge on the resources devoted to the storage of goods, but also on the interest rates considered by shipper when discounting the capital costs. As a consequence, we approximate inventory costs with the goods' value

density, a common practice in the literature. As made clear in Table 1, these two explanatory variables of the shipment size are qualitatively similar in France and Germany. Yet, the higher annual flow of commodities observed in Germany (1,845 tons/year vs. 1,784 tons in France) and the lower value density of goods in that country (11,311 euros/ton vs. 14,382 euros/ton) are consistent with the theory, stressing the opposite effects of these variables on the optimal shipment size (see equation (7)). However, it is noticeable that differences in averages are not that pronounced¹², even if standard deviations are larger in France. This observation is again in line with the wider sectoral coverage of the French ECHO survey.

Concerning the other variables used to estimate the extended EOQ model in equation (9), we notice that German shipments are sent over longer distances (+68%). Given the higher area of France (544,000 km² vs. 349,000 km² in Germany), a potential explanation comes from the fact that French economic actors are more prone to favor "neighbor" relationships. Moreover, this larger distance figure is consistent with the slightly higher share of international shipments observed in Germany (14% vs. 12.7% in France).¹³ Lastly, the goods'

¹² This conclusion must be moderated if one considers the average inflation rate of 1.6%/year in France over 2005-2013. Expressing the 2005 value density of goods in 2013 euros, we find 16,590 euros/ton, i.e. 46% more expensive than in Germany.

¹³ It may also be the case that the sampled German firms are more concentrated in some regions (raw material for instance), thus generating longer traveled distances if the customers are uniformly distributed over the national territory.

characteristics and their logistical requirements¹⁴ are quite different across countries, even if the pallets are the main way to condition the shipments both in France (55%) or Germany (44%) and temperature-controlled vehicles are used in a similar proportion (10%). Given the activity sectors of the asked firms, voluminous and dangerous shipments are more represented in the German sample (31% and 13% respectively vs. 6% and 3% in France). By contrast, French carriers send more food items and are more likely to condition the shipments as bulks (28% and 17% respectively vs. 12% and 8% in Germany).

Based on these data, three econometric models of the shipment size were successively estimated via OLS, for each country separately. The outcomes are presented in Table 2. Because the (dependant and explanatory) continuous variables have been transformed as logs, the estimated parameters correspond to elasticities. We first discuss the results as compared to the theoretical predictions, with a few references to national specificities. In a second step, we contrast the main parameters quantitatively and we address the issue of models transferability, in order to introduce the comparative discussion in Section 5

4. Empirical analyses

Table 2. Determinants of the (log of) shipment size

Country	France	Germany	France	Germany	France	Germany
<i>Models</i>	<i>(I)</i>		<i>(II)</i>		<i>(III)</i>	
Ln(Annual flow)	0.441*** (0.007)	0.435*** (0.022)	0.435*** (0.007)	0.430*** (0.022)	0.422*** (0.007)	0.431*** (0.021)
Ln(Value density)	-0.311*** (0.014)	-0.108*** (0.020)	-0.343*** (0.015)	-0.133*** (0.020)	-0.320*** (0.015)	-0.138*** (0.021)
Ln(Distance)	-	-	0.134*** (0.016)	0.203*** (0.039)	0.095*** (0.014)	0.164*** (0.043)
International shipment	-	-	-	-	0.400*** (0.066)	0.114 ^{ns} (0.091)
Food	-	-	-	-	-0.016 ^{ns} (0.049)	-0.201* (0.112)
Bulk	-	-	-	-	0.590*** (0.065)	0.010 ^{ns} (0.114)
Pallets	-	-	-	-	0.437*** (0.046)	0.020 ^{ns} (0.060)
Dangerous	-	-	-	-	0.128 ^{ns} (0.094)	-0.107 ^{ns} (0.087)
Temperature-controlled	-	-	-	-	-0.886*** (0.066)	-0.241** (0.120)
Fragile	-	-	-	-	-0.100 ^{ns} (0.066)	-0.002 ^{ns} (0.080)
Voluminous	-	-	-	-	0.248*** (0.088)	-0.092 ^{ns} (0.065)
Constant	0.948*** (0.123)	0.161 ^{ns} (0.259)	0.565*** (0.132)	-0.789** (0.311)	0.318** (0.140)	-0.473 ^{ns} (0.331)
Observations	3,486	487	3,486	487	3,486	487
F-stat	4,821.2	312.7	3,237.0	228.7	1026.2	66.0
Adjusted R²	65.89	56.19	66.86	58.43	70.26	59.52

Notes: Standard-errors in brackets; ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$; ^{ns}: non-significant.

¹⁴ A given shipment may be characterized by two (or more) control variables. For instance, food items can be sent under temperature-controlled conditions.

Starting with the basic EOQ model (see equation (8)), the estimates are consistent with the theory: the larger the annual flow of commodities linking a shipper to its client and the lower the inventory costs (approximated by the value density of goods), the higher the shipment size. It is worth noting, however, that the estimated parameters do not reach the expected value of $|0.5|$, especially for what concerns the value density. Whereas the shipment size will increase by 0.44% if the annual flow rises by 1%, it will decrease by 0.31-0.11% only (and not 0.5%) if the value density of the shipped goods grows in a similar extent.¹⁵ Moreover, the potentially positive impact of the unobserved ordering and fixed transport costs is only confirmed for France because the constant term is not statistically different from zero with the German data.¹⁶ This first model explains a non-negligible share of the observed variance in shipment sizes, especially for France where the adjusted R^2 is equal to 65.9% (56.2% in Germany).

Model (II) additionally considers the influence of the traveled distance. As argued by some authors [25, 26, 22], we do observe one positive relationship between the size of the shipments and the length of the trips necessary to deliver the clients. Whereas the corresponding elasticity is quantitatively small (it ranges from 0.13 to 0.20), adding the road distance as an explanatory variable does not strongly affect the parameters associated with the annual flow of commodities and their value density. By contrast, the second model shows a reduced influence of the constant term in France, which even becomes significantly negative in Germany. Even if small in magnitude, the increase in the adjusted R^2 observed for both countries suggests that considering the traveled distance as a determinant of the shipment size is relevant.

The last model includes a set of dummies describing the goods' characteristics and some logistical features of the shipments. We here observe mixed results. Aside from dangerous and voluminous shipments, estimates have the same sign in both countries, even if they are more often significant for France.¹⁷ Thus, temperature-controlled, fragile or food shipments tend to be smaller than the average while those conditioned as bulks or pallets are larger. Interpreting these results as proxies of the ordering and fixed transport costs is not obvious. On the one hand, we may expect that temperature-controlled shipments are, for instance, more expensive to prepare and to condition than others, which should theoretically

increase the shipment size. On the other hand, temperature-controlled products are likely to be more expensive to store, which potentially decreases shipment size. As a consequence, these characteristics are probably more useful to study the determinants of the shipment size that not integrated into the structural EOQ model. By contrast, the positive sign associated with the international shipment variable is consistent with the explanation based on ordering costs. All in all, we believe these control variables to be informative about the heterogeneity in shipment sizes. This belief is reinforced by the increase in the adjusted R^2 shown in Table 2, especially for France where it reaches 70.3%, but also by the apparent stability of the other parameters.¹⁸

As argued in the Introduction, one objective of this article is to discuss the differences between the main determinants of the shipment size in France and Germany, in order to question the transferability of this logistics behavior model. The results presented in Table 2 illustrate that the annual flow of commodities, the goods' value density and the traveled distance have qualitatively similar, although differentiated, influences on the shipment size choice. What about their quantitative differences?

A first way to realize such comparative exercise is to go beyond the point estimates shown in Table 2 and to look at the parameters' confidence intervals. This information is useful because econometric results are always characterized by varying precisions. Put differently, one cannot conclude that parameters significantly differ across countries without checking if they share (or not) some common statistical support.

¹⁵ The difference between the estimated elasticity of the shipment size w.r.t. value density and the theoretical one (of -0.5) may be explained by missing information on storage costs and on the interest rate used by carriers to calculate immobilization costs. Actually, we are approximating inventory costs only with the goods' value density. See the discussion in Section 5.

¹⁶ The constant term will be positive only if fixed costs o_i are larger than 1. Since we do not really observe these costs, despite the inclusion of control variables in model (III), it is probably better to view the constant term as a way to capture the other (non-structural) determinants of the shipment size.

¹⁷ The higher heterogeneity in shipment sizes linked to the goods' characteristics found in France is probably due to the larger spectrum of economic activities covered by the ECHO survey, but also to the larger number of observations used for estimates.

¹⁸ Apart for the elasticity of the shipment size w.r.t. the traveled distance. Due to the high correlation between latter variable and the dummy characterizing the international shipments, the parameters estimated for the traveled distance strongly decrease in model (III).

Table 3. Differences in estimates (based on model (II))

Country	France		Germany		Test Stat.	Signif.
	LB	UP	LB	UP		
<i>Statistics</i>						
Annual flow elasticity	0.419	0.450	0.381	0.478	0.2166	ns
Value density elasticity	-0.375	-0.310	-0.178	-0.089	8.4000	***
Distance elasticity	0.098	0.170	0.117	0.289	1.6368	ns
Constant	0.269	0.860	-1.459	-0.119	4.0077	***

Notes: LB: lower-bond; UP: upper-bond; Confidence intervals have been computed at the 97.5% level; For the test: ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$; ns: non-significant.

For the sake of consistency with the following discussion on transferability, figures in Table 3 are based on results from model (II). They highlight that the goods' value density is the only structural determinant which has a differentiated impact on the shipment size. Thus the elasticities of the annual flow and those of the traveled distance crisscross together. Given the larger size of the sample, the range of estimates is smaller for France and the confidence intervals are almost entirely comprised within those found for Germany. By contrast, the upper and lower bounds of the value density elasticities do not share any common statistical support. From these results, one can conclude that French and German firms do not put the same weight on inventory costs when choosing the shipment size. These findings are confirmed by the

statistical tests presented in the two last columns of Table 3 which look at the differences in single regression coefficients [34, 35].¹⁹ We thus observe that elasticities of the shipment size w.r.t. the annual flow and the traveled distance are not statistically different for both countries, as opposed to those linked to the value density variable which strongly differ across datasets.²⁰

In our cross-country perspective, it may also be interesting to assess the different contributions of available information to the overall variance in shipment sizes observed in the data. Table 4 presents the results of one ANOVA performed on model (III).²¹

Table 4. Variance analysis of model (III)

Country	France				Germany			
<i>Statistics</i>	<i>PSS</i>	<i>SoV</i>	<i>DoF</i>	<i>Signif.</i>	<i>PSS</i>	<i>SoV</i>	<i>DoF</i>	<i>Signif.</i>
Ln(Annual flow)	7,247	47.8%	1	***	247.53	53.8%	1	***
Ln(Value density)	680	4.5%	1	***	11.82	2.6%	1	***
Ln(Distance)	67	0.4%	1	***	10.66	2.3%	1	***
International shipment	431	2.9%	1	***	0.60	0.1%	1	ns
Food	425	2.8%	1	***	4.13	0.9%	1	***
Bulk	688	4.5%	1	***	0.09	0.0%	1	ns
Pallets	480	3.2%	1	***	0.01	0.0%	1	ns
Dangerous	52	0.3%	1	***	1.04	0.2%	1	ns
Temperature-controlled	181	1.2%	1	***	1.25	0.3%	1	*
Fragile	211	1.4%	1	***	0.02	0.0%	1	ns
Voluminous	194	1.3%	1	**	0.90	0.2%	1	ns
Residuals	4,491	29.7%	3,474	-	182.04	39.6%	475	-

Notes: PSS: partial sum of squares; SoV: share of variance explained by the variable; DoF: degrees of freedom.

¹⁹ The test used here to check if the parameters significantly differ follows a Gaussian distribution and applies to large sample studies. Considering e.g. the annual flow parameter β and using subscripts F and G for France and Germany respectively, the test statistic is

$$Z = \frac{\beta_F - \beta_G}{\sqrt{SE(\beta_F)^2 + SE(\beta_G)^2}}$$

²⁰ The same can be said for the intercepts, that do not share any common support and that are significantly different for both countries.

²¹ For both models, a type I ANOVA is performed which sequentially includes variables and tests successively the portion of their additional explained sum of squares. As in both models the order of variables is the same, a comparison of variables' contribution to the explanatory power is valid.

This statistical analysis shows us that the strength of the commercial relationship linking a carrier to its client is, by far, the main determinant of the heterogeneity in shipment sizes. As such, the annual flow of commodities sent to a given receiver accounts for 54% of the shipment size variance observed in Germany (48% in France). The value density of goods appears to be the second influential factor, even if results are somehow mixed in this respect: for Germany, this characteristic of the shipments does not really dominate the influence of the traveled distance (2.6% and 2.3% of the explained variance respectively); for France, it has a similar impact than bulk conditioning²² (4.5%). Lastly, goods' characteristics or logistical features have a non-negligible explanatory power in France (especially food, pallets and international shipments) whereas they do not influence the variance in shipment sizes observed in Germany. To summarize, the ANOVA shows that the annual flow variable contributes, by far, to the highest portion of the explained variance when estimating shipment sizes. As the parameters of this variable are almost identical in both countries (see Tables 2 and 3), the application of the models in varying circumstances may be promising.

In order to propose a sound analysis of the shipment size models transferability, we conclude this empirical investigation by looking at two main statistical indicators which reflect the magnitude of predictions' errors when applying parameters estimated in one context to other data, namely the "root mean squared error" (RMSE) and the "mean absolute error" (MAE):²³

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}} ;$$

$$MAE = \frac{\sum_{i=1}^n |\hat{y}_i - y_i|}{n} \quad (10),$$

where y_i is the observed (logarithm of) shipment size; \hat{y}_i is the value predicted when transferring the parameters found in one place-period (Germany in 2013 for instance) to one other circumstance (France in 2004-2005); and n is the number of observations to be used.

With X_i denoting the vector of relevant explanatory variables in country i and using subscripts F and G for

France and Germany respectively, the "basic" transferred model is:

$$\hat{y}_F = \hat{\alpha}_G + X_F \cdot \hat{\beta}_G ;$$

$$\hat{y}_G = \hat{\alpha}_F + X_G \cdot \hat{\beta}_F \quad (11).$$

[6] argue, however, that for discrete choice models the alternative-specific constants (and the measurement scales) are less transferable than the relative parameters; they should be adjusted whenever possible. As the intercept of the OLS regression has a similar function than the alternative-specific constants (i.e. it guarantees a correct average of the dependent variable, in line with the data used for estimation), updating the intercepts may be relevant:

$$\hat{\alpha}_F^U = \bar{y}_F - \bar{X}_F \cdot \hat{\beta}_G ;$$

$$\hat{\alpha}_G^U = \bar{y}_G - \bar{X}_G \cdot \hat{\beta}_F \quad (12),$$

where \bar{y}_F and \bar{y}_G are the averages of the (log of) shipment size in France and in Germany; \bar{X}_F and \bar{X}_G are vectors characterizing the mean values of significant explanatory variables.

The updated constants in combination with the transferred coefficients can then be used to predict the dependent variables more precisely:

$$\hat{\hat{y}}_F = \hat{\alpha}_F^U + X_F \cdot \hat{\beta}_G ;$$

$$\hat{\hat{y}}_G = \hat{\alpha}_G^U + X_G \cdot \hat{\beta}_F \quad (13).$$

Table 5 synthesizes the results of this transferability analysis performed on model (II).²⁴ According to [7], models are never perfectly transferable, due to imperfect functional specifications notably: the degree of transferability should be addressed rather than treating transferability as a dichotomous outcome. Since RMSE and MAE indicators do not have any specific threshold stating the prediction accuracy is "good" or "bad", measurements made on the transferred models can be compared w.r.t. their benchmark values.

²² The ANOVA does not postulate any linear relationship between the outcome of interest (shipment size) and the explanatory variables. Put differently, the ANOVA can display a significant impact of a given variable on the shipment size whereas this variable is not statistically significant in the OLS model.

²³ The MAPE ("mean average percentage error") is suboptimal in this case because some of the observed shipment sizes are equal to 1 and thus the actual value $\ln 1$ becomes 0, leading to a non-calculable measurement.

²⁴ The additional control variables in model (III) reveal very different signs and insignificancies between countries (Table 2). In addition, they have a very low explanatory power (Table 4) and, from a practical point of view, they may be hardly available in dedicated freight surveys or statistics.

Table 5. Transferability analysis (based on model (II))

<i>Models</i>	Benchmark		Basic transfer (equation (11))		Updated constant (equation (13))	
<i>Country</i>	France	Germany	France	Germany	France	Germany
<i>R</i>²	66.9	58.7	63.8 (-4.6%)	53.7 (-8.5%)	63.8 (-4.6%)	53.7 (-8.5%)
<i>RMSE</i>	1.200	0.625	1.400 (+16.7%)	0.961 (+53.8%)	1.286 (+7.2%)	0.719 (+15.0%)
<i>MAE</i>	0.943	0.485	1.121 (+18.9%)	0.784 (+61.6%)	1.028 (+9.1%)	0.575 (+18.6%)

Notes: Percentages in brackets refer to deviations w.r.t. benchmark values.

As made clear in Table 5, the R^2 of the simple OLS regressions between the observed and the predicted values are quite high and similar from their reference values.²⁵ Then considering the basic transfer process (equation (11)), it appears that crossing German parameters with French data does increase, but moderately, the predictions' errors: RMSE and MAE grows by 17% and 19% respectively as compared to their benchmark values. Despite this promising result, the simple transferability of French coefficients on German data is not obvious, given the large increases in RMSE and MAE shown in Table 5 (+54% and +62% respectively).

In a second step, we apply equation (13) and we notice that RMSE and MAE measures are now quite similar from their benchmark values, even for the German case where the RMSE and MAE growths are clearly not excessive (+15% and +19% respectively). Updating the constants - which is a common approach [9] as they tend to be the least transferable part of the model and they significantly differ in our case study (see Table 3) – thus ensures almost similar prediction quality than originally. All in all, we believe latter results support the transferability of the shipment size models between France and Germany.

5. Discussion

Our empirical analyses have shown that the datasets are consistent with the theory for both France and Germany: the coefficients are significant and have the same expected signs. Moreover, previous calculations have demonstrated that models transferability cannot be rejected, even if we have noticed slight differences between the models estimated against the French and the German datasets. We now discuss possible causes for these differences. Three families of causes are identified: differences in the survey perimeters and/or in the structure of the samples; differences in the costs structure of road freight transport; and differences in the inventory costs.

The first potential explanation for these differences is due to distinct perimeters and varying structures of the samples. For instance, raw materials extraction establishments were excluded from the sampling in the French ECHO survey, whereas they were included in the German survey. The logistics requirements for raw material extraction, transport and processing is highly specific. This could explain, to a certain extent, the differences in the models' results, in particular the reduced influence of the value density. Remind that the value density is a proxy for the opportunity cost for the firm to hold the commodities; for raw materials warehousing and depreciation costs can be extremely low. The "bulk" variable controls for this effect, but only partially. Also, shipments of less than one ton were excluded from the German dataset, while they constitute more than half of the shipments of the French dataset. The transport techniques and costs differ a lot between small and large shipments.

The second potential, but closely related, cause for the differences between the French and the German estimates relates to the structure of the transport costs. In particular, the EOQ model presented in Section 2 and estimated in Section 4 ignores the capacity constraint of vehicles. Yet, the traveled distance (models (II) and (III)) may serve as a proxy for vehicle types, but it does not really consider the maximal load weight of the shipments. Since shipments in the German dataset are on average substantially larger than in France (see Table 1), this constraint is likely to hold more often in the German dataset. Ignoring this constraint most certainly causes a bias in the estimated parameters, although it is not easy to predict in which direction.

In the same logic, our estimates do not control from potential differences in terms of transport cost between the two countries (France and Germany) and the two periods (2004 and 2013). This is not easy to control for such an evolution in the frame of the EOQ model: transport cost does not appear formally in the model, it is only the fixed share of the transport price (i.e. the share of the transport price which does not depend on shipment

²⁵ For a given country, the R^2 is the same for the updated and for the basic transferred model as only the constant is varied. This implies a simple shift of the forecasted values, but no change in variance explanation. Moreover, applying the French model to German data we get a correlation coefficient of 0.73, which indicates that there is a strong relationship between observed and predicted values. The same exercise on French data with German parameters leads to a correlation coefficient of 0.80.

size) which plays a role. In addition, fixed cost directly incurred by the shippers when dispatching a shipment (preparing orders, conditioning, loading and unloading, administrative tasks) also plays a role, and cannot be directly measured. Finally, the type of vehicles used for transport should also be controlled for: road transport is not a homogenous activity; there are a wide variety of vehicles, transport organizations, etc., only partially mirrored by the explanatory variables of the models estimated in this paper.

The third potential cause for the observed differences, which may explain the substantial variation of the value density elasticity (see Table 3), is related to the inventory cost. This cost describes the willingness of the shipper to pay so that commodities spend less time in the firm between the moment they are produced and the moment they are sold. These inventory cost consists of the warehousing cost and the opportunity cost of capital associated with the commodities. Given the fact that these variables are not measured accurately, the value density of the shipments has been used as a proxy for the inventory cost.

Differences in warehousing costs can theoretically explain the discrepancy between the French and the German datasets. Comprehensive information on warehousing costs is not available for Europe, but some elements of comparison exist. For example, [36] observes a spread between the rents in Paris (about 7.5€/sq m/month) and Munich (about 6.6€/sq m/month) and even Berlin (about 5.7€/sq m/month). This is, however, not completely consistent with other data sources. For example, [37] confirms that the Paris Region is one of the most desirable logistics locations, but this is the only region in France, whereas several regions in Germany are in the top category. Also, the World Bank's Logistic Performance Index of France is lower than that of Germany. All in all, it does not seem that the national differences in the warehousing markets can fully explain the difference in the parameter of the value density in the German and French models.

Another possible explanation is the cost of money for shippers: commodities in warehouses or in transport represent an opportunity cost, the cost of the corresponding liabilities. This is probably related to the value density of the commodities: the cost of holding a ton of smartphones over a certain period of time is probably much higher than the cost of holding a ton of cement over the same period of time. However, the value density is not the only driver of the inventory costs: the interest rate at which the firm can obtain money is also critical.

This interest rate varies a lot between firms: it depends on the share of debts and capital in the firm's liabilities, and their own interest rates, which in turn depend on the firm's activity sector and on the firm's particular financial health and growth perspectives. A decrease in the interest rates would explain the lower sensitivity to value density in the German dataset compared to the French dataset. Global macroeconomic indicators, however, do not confirm unambiguously this line of thought. For example, it is true that the German (resp. French) government bonds over 10 years have decreased from 4.3% (resp. 4.3%) to 1.3% (resp. 2%) between 2004 and 2013.²⁶ However, the implied market return has stayed relatively constant over the same periods in the two countries (from 7.64% to 8.46% in Germany and from 7.56% to 9.11% in France²⁷), the decrease in the cost of debt being compensated by the increase in the market risk premium. Also, the financial structure of French and German firms is both similar and stable over the 2004 to 2013 period, with a ratio of assets to equity of about 320% [38]. The mere decrease in the government bond rates from 2004 and 2013 does not appear to be able to explain alone the differences between the elasticities found for France and Germany models. As a consequence, a more in-depth analysis is needed in order to further investigate the influence of the cost of money for firms in the choice of shipment size.

A final explanation is that warehousing costs and the opportunity cost of capital are not the only reasons a shipper would be willing to pay to avoid having commodities in storage. Let us quote two possible additional causes. The first one is depreciation: goods such as groceries, or fashion, are subject to physical or economic depreciation due to which shippers will prefer to limit storage duration, and thus increase shipment frequency. The second one is uncertainty: uncertainty in final demand, combined with a large sensitivity of customers to shortages, may induce shippers to increase shipment frequency in order to improve the reactivity of their supply chains, and thus both reduce inventory costs and customer dissatisfaction. Obviously, value density cannot capture all these variations alone, and even the addition of dummy variables as in model (III) is not sufficient to explain them fully.

All in all, the causes of the differences between the French and the German results are multiple. The datasets at hand and the quite simple estimation procedures applied in this paper are unfortunately not precise enough to make the models fully consistent, or to identify unambiguously the causes of the differences. The results of the estimation show that the behavior of shippers in France and Germany in 2004 and 2013 are globally consistent and also reveal similar forecasting results

²⁶ <http://www.tradingeconomics.com/france/government-bond-yield> and <http://www.tradingeconomics.com/germany/government-bond-yield> (last accessed 24th of February 2017).

²⁷ <http://www.market-risk-premia.com/de.html> and <http://www.market-risk-premia.com/fr.html> (last accessed 24th of February 2017).

when models are applied to distinct circumstances (especially for the case of updated constants). Nonetheless, a fully transferable EOQ model including all strategic key variables does not appear to be yet available.

6. Conclusion and outlook

A shipment size model explains observed transport behavior (mode choice, vehicle choice) by the annual flow of goods, and in addition, by the capital costs and some other attributes of the commodities themselves. Assuming the availability of information on the distribution of the flow of goods in transport planning areas, shipment size models open the door to transfer behavior models in freight from one region to another.

In this article, we have assessed this transferability exemplarily for the cases of Germany and France. It turned out, that the flow of goods exchanged between a shipper and its client has a surprisingly similar impact on the chosen shipment size in both countries. This is a first indication of a certain universality of the rational core of this behavioral model. In addition to that, the forecasting accuracy of the transferred model supports the models transferability. In contradiction to that, the impact of inventory costs differs considerably, but this does not contradict the rational core of the behavioral model. Thus, the coefficients of this variable can be adjusted for the purpose of calibration and interregional transfer as well as for forecasting purposes. For such an adjustment, the gap between the elasticities needs to be bridged. A possible tool could be the application of indices concerning the development of capital procurement costs. Nevertheless, using such indices potential biases may also occur. Out of that reason, further empirical knowledge is necessary to determine the underlying motives. The impacts of firm-specific logistics variables are similar between Germany and France, however, these variable have little explanatory power. In a strategic model, they could even be omitted. Another approach is used by [13] who build homogenous segments with respect to such logistics variables and therefore increased the explanatory power of shipment size choices modeling.

In summary, the knowledge about the distribution of micro freight flows is crucial when it comes to the transfer of behavioral models in freight, and this can be seen as the most important message for those institutions that are in charge of monitoring freight markets through CFS.

There are several future research directions in order to overcome some of the limitations identified in the preceding discussion. The first one would be to improve the representation of the transport costs, by introducing formally the capacity constraint of vehicles, and also by distinguishing vehicle types. This requires adapting the

shipment size estimation procedure but also better data on the transport operations. The second improvement would concern the representation of inventory costs, something which can be done in several ways: first, by measuring warehousing costs; second, by introducing data about the financial structure of shippers; third, by an even more precise segmentation of commodity types, in order to better account for logistical constraints, and depreciation in particular; fourth, by introducing information on the variability of the demand (for example by measuring the safety stock). All these research directions imply improving the theoretical models and the estimation procedures, and also better data. With that respect, it should be noted that a new CFS is currently being collected in France, which may make some of these objectives reachable.

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