1. Introduction

The main feature of recent national freight transport models in Europe is the incorporation of a logistic component (module) in the traditional freight demand-modelling framework (de Jong et al. 2013). Logistics decisions of firms are incorporated in the modelling process often based on shipment size optimization theory.[1] According to this theory, firms are assumed to minimize total annual logistics costs by trading-off inventory holding costs, order costs and transport costs. The logistics module estimates frequency/shipment size choice and transport chain choice (i.e. transport mode choices and use of trans-shipment)[2] based on a cost minimization model where firms are assumed to minimize annual total logistics costs.

Such logistics modules have been developed for Norway, Sweden (SAMGODS model), Denmark and Flanders (see Ben-Akiva and de Jong, 2013), within the overall framework of the aggregate-disaggregate-aggregate (ADA) freight transport model.[3] The current logistic modules in these countries, however, lack two main elements. First, they do not account for the main determinants of shipment size and transport chain choices other than cost, i.e. decisions are mainly based on cost considerations (and to some extent on factors such as access to road and rail and value densities). Second, these models are deterministic and lack a stochastic component. A deterministic model has a weak empirical foundation: the way transport agents (i.e. shippers, forwarders and carriers) behave in the model is not based on observed data but on the assumption that they will choose the shipment size and transport chain that has minimum costs (and on data relating to transport networks, possible transhipment locations and expert knowledge of cost functions). Instead of observed behaviour, such a model represents normative behaviour. In order to improve the predictions of the model and allow richer and more realistic policy analyses, logistics decisions should be modeled taking into account these two elements.

The main objective of this paper is estimating a full random utility logistic model, i.e. stochastic model, for Sweden, which overcomes the aforementioned shortcomings of deterministic models.

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[1] See Chow et al (2010) for a comprehensive review of freight forecast models elsewhere.

[2] A transport chain is defined here as a series of modes that are all used to transport a shipment from the sender to the receiver (e.g. road-sea-road).

[3] Moreover, models for shipment size and mode choice have been developed based on the French ECHO dataset at the shipment level (Combes, 2010).

A deterministic model effectively assumes that the stochastic component can be ignored – in other words, that the researcher has full knowledge of all the drivers of behaviour and that there is no randomness in actual behaviour. As a result of adding a stochastic component in the utility model, the response functions (now expressed in the form of probabilities) become smooth instead of lumped at 0 and 1 as in a deterministic model. This in turn addresses the problem of "overshooting"[4] that is prevalent in a deterministic model when testing different policies. Stochastic models of mode and shipment size choice have been estimated before (see footnote 3), but usually the estimation is not by commodity type and a systematic comparison between stochastic and deterministic models in an implementation context (e.g. in terms of elasticities calculated from runs with the actually used models) is missing.

The empirical analysis in this paper involved two steps. As a first step, we estimated econometric models that describe the determinants of transport chains and shipment size choices. We used the 2004/2005 Swedish Commodity Flow Survey (CFS)[5] and inputs from the SAMGODS model for estimation of multinomial logit models (MNL) for 16 different commodity groups. Parameter estimates from this model were later used to setup a fully stochastic model. Note that by their very nature the MNL models are probabilistic models because they include a stochastic component to account for the influence of omitted factors. The main results from the MNL models show that variables such as transport cost and time, having access to rail or quay at origin and distance are important determinants of shippers' mode and shipment size choices.

As a second step, based on the MNL estimation results, we setup a stochastic logistics model for two commodity groups, metal products and chemical products. Using this model, we compared transport cost and time elasticities for tonne-km between the stochastic and deterministic models for the two commodities. These elasticities differ between the two models. Most importantly, they are usually smaller (in absolute values) in the stochastic model which implies "overshooting" is less of a problem than it is for deterministic models, as expected. In future endeavors, the difference between the two models could be further studied by looking at

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[4] "Overshooting" happens when the relevant part of the logistics costs function is rather flat and a small change in logistics costs can lead to a shift to a completely different optimum shipment size and transport chain (Abate et al. 2014). On the other hand there could also be "sticky" choices in a deterministic (all-or-nothing) model when one alternative is clearly cheaper than the other alternatives. Improving the other alternatives will then not lead to any change in market shares until one of these other alternatives becomes the cheapest and then the deterministic choice is suddenly completely altered.

[5] http://www.trafikverket.se/contentassets/23a269d514d24920ad445881d724811f/filer/vfu_2004_2005.pdf

elasticities on other output measures such as vehicle kilometers, number of vehicles crossing a screenline, etc.

The remaining part of this paper is organized as follows. Section 2 presents the econometric model set up and results from estimation; Section 3 describes the stochastic model setup based on the inputs from Section 2; Section 4 compares model outputs from the stochastic and deterministic models; finally, Section 5 presents our main conclusions and suggestions for future work.

2. Econometric framework

Econometric studies of freight mode/vehicle choice are based on the key insight that mode/vehicle/cargo unit choice entails simultaneous decisions on how much to ship (see, for example, Abate and de Jong, 2014; Johnson and de Jong, 2011; Holguin-Veras, 2002; Abdelwahab and Sargious, 1992; Inaba and Wallace, 1989; McFadden et al., 1985). This simultaneity in decisions requires the use of joint econometric techniques such as discrete-continuous models. An alternative is sometimes discrete-discrete (by classifying shipment sizes to a number of size classes), as in Johnson and de Jong and (2011) and Windisch et al. (2010). In addition to recognizing this simultaneous decision process, these studies show that various haul, carrier, and commodity characteristics affect the decisions regarding the optimal shipment size choice and choice of transport mode.[6] The discrete choice is usually mode choice, but can also be the choice of transport chain (e.g. Windisch et al., 2010).

McFadden et al. (1985) and Abdelwahab and Sargious (1992) provide the most complete formulation of the firm's simultaneous choice of mode and shipment size. However, the applicability of their models is rather limited when decision makers have to choose from more than two mode alternatives. Holguin-Veras (2002) and Johnson and de Jong (2011) used an indirect approach to address the simultaneity problem. They model the discrete choice component (vehicle class choice in Holguin-Veras and mode choice in Johnson and de Jong) as the main equation, replacing actual shipment with prediction from a shipment size auxiliary regression. This approach is an interesting one when the main focus is the vehicle/mode choice because it is possible to apply advanced discrete choice models that overcome the independence of irrelevant

[6] In this study, as in most previous studies, we consider the weight of shipment size as an endogenous variable. However, we note that shipment volume (in m^3) is also an important factor, which shippers consider jointly with mode choice decisions. We cannot model shipment volume because our data set, the Swedish CFS, does not contain this information.

alternatives (IIA) problem. But, unlike McFadden et al. (1985), this approach does not allow for testing for simultaneity bias.

Due to the above technical complexities, mode choice in freight transport is usually studied in isolation (or in combination with network assignment, as multi-modal assignment). However, as pointed out by Johnson and de Jong (2011), mode and shipment size are closely linked choices. Large shipment sizes usually coincide with higher market shares for non-road transport, whereas there is a high correlation between road transport and small shipment sizes. Such a correlation calls for a joint econometric model. Abate et al. (2014) tested two types of joint econometric models, namely: a discrete-discrete (DD) model where the dependent variable is a discrete combination of shipment size categories and mode choice alternatives, and a discrete-continuous (DC) model which treats transport mode chain choice as a discrete variable and shipment sizes as continuous variable. Although DC models were found to be theoretically sound, given the size of the CFS data and the number of commodity groups involved, a pragmatic alternative is a DD model. In this paper we estimate a DD which is specified as follows:

$$U_i = \beta X_i + \varepsilon_i \tag{1}$$

Where U_i is the utility derived from choosing a discrete combination of transport chain and a shipment size category i, X_i is a vector of independent variables explaining mode choice and shipment size choice, β is a vector of parameters to be estimated and ε_i is an error term. Since U_i is a joint variable, the model setup allows for simultaneous consideration of transport chain and shipment size decisions. The main variables included in X_i are transport cost, transport time, infrastructure access indicators, value density, and domestic/international shipment indicators. We estimate Eq. 1 using a multinomial Logit model (MNL).

We note that there could be correlations between alternatives, especially given that there are alternatives that have a transport chain (or a shipment size) in common. The MNL model assumes choice alternatives are independent, and therefore could suffer from the 'red bus – blue bus' problem (that is that similar alternatives should have higher cross-elasticities, but do not have these in MNL). A relatively straightforward solution in such cases is the nested logit model. Windisch et al. (2010) tested various nested logit models on the CFS 2004-2005 (but not by commodity) and found that a nesting structure with transport chain choice above shipment size choice worked best (this means that there is more substitution between shipment sizes than between modes). More complicated nesting structures can be tried in mixed logit and multivariate probit models, but these model types have very long run times, especially on large data sets as we have here.

2.1. **Data**

The main data source for this paper is the 2004/2005 Swedish Commodity Flow Survey (CFS). The data has 2,986,259 records. Each record is a shipment to/from a company in Sweden, with information on origin, destination, modes, weight and value of the shipment, sector of the sending firm, commodity type, access to rail tracks and quays, etc.[7] From this we selected a file of around 2,897,010 outgoing shipments (domestic transport and export, no import) for which we have complete information on all the endogenous and exogenous variables.

Although the CFS data is extensive, it does not contain information on transport costs and transport time variables. Given the importance of these variables in mode/shipment size choice analysis, the existing logistic module of the deterministic model was used to generate them for each shipment in the CFS. They were generated both for the chosen mode-shipment alternatives in the CFS and for potential non-chosen alternatives tailored to each shipper based on the transport network of the origin and destination of their shipment.

The CFS classifies transport mode chains to chains inside Sweden and chains outside Sweden. In domestic shipments, trucking accounts for the overwhelming majority of the shipment frequency (95.79%), followed by chains which involve waterborne transport modes (a ship vessel and ferry).[8] The high share of trucking is also evident in its percentage share in weight and value in domestic freight transport. For international shipments, vessel (maritime) transport accounts for the highest share both in shipment weight and value.

To see the distribution of shipment sizes we classified the weight variable in the CFS into 16 categories[9], as shown in Table 1. A quarter of the total shipments fall in the first category (0-50

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[7] In the CFS a shipment is defined as a unique delivery of goods with the same commodity code to/from the local unit or to/from a particular recipient/supplier (SIKA, 2004).

[8] We defined transport chain alternatives based on their frequency in the CFS. Transport chains that occurred with a frequency of 96 or higher were considered as possible choice options.

[9] The dependent (choice) variable (U_i) in Equation 1 is defined based on the classification on Table 1.

kg). The prevalence of small shipments reflects the dominance of trucking which is usually preferred for its flexibility and reliability. Categories 10 and 11, ranging from 35 to 45 tonnes (well within a full truckload range), account for 23.71 %, again showing the dominant role of trucking.[10]

Figure 1 presents the cumulative density distribution of shipment weight for metal products and chemical products and for all commodities in the CFS. Shipments weighing 10 tonnes or less account for about 90% of the shipments for the two product groups. This distribution is somewhat different from what is observed for all commodities which also have concentration of larger shipment sizes.

There are 24 commodity groups in the CFS. In this paper, however, we found it to be more instructive to analyze selected commodities than all commodities identified in the CFS. This is due to the dominance of trucking for most shipments. In fact, for ten commodity groups the share of trucking is more than 98 %. Clearly, there is little to learn about the determinants of mode choice decisions of shippers when there is such overwhelming dominance of one mode of transport. For the remaining 16 commodity groups, including metal products and chemical products for which we implemented a stochastic module, there is relatively less dominance of trucking.

Descriptive statistics are presented in Table 2. On average, 2 % of all shippers had access to rail at origin and 0.4 % had access to quay at origin. The equivalent figures for metal products and chemical products are 57 and 0.03 % for rail access, and 0.5 and 0.03 % for quay access, respectively. Much to the benefit of the econometric analysis, the CFS has an extensive variation in terms of average shipment values, shipment weights, and transport cost and time.

2.2. **Econometric results**

Table 3 presents estimation results from the MNL model presented in Equation 1 for 16 commodity groups. The choice alternatives in each model are a discrete combination of a transport chain and shipment size. By and large, the results reported in Table 3 are plausible and

[10] The maximum gross weight of the trucks is 60 tonnes in Sweden and Finland compared to 40 tonnes in most other European countries

are in line with expectations. Transport cost has a negative effect on the utility of a choice alternative. This is in line with theory which predicts that higher delivery costs make a choice alternative less attractive. While these effects are statistically significant, the parameter values are often small, which can imply that cost has a rather limited influence on a choice alternative. It is important to note, however, that both the unit of measurement and dimensions of change contribute to this low level estimates.

We used a single cost coefficient for all alternatives, building on the idea that 1 SEK is 1 SEK, whatever the alternative it is spent on. Other forms than linear could be tried for the cost specification (such as logarithmic, spline or a combination of linear and logarithmic), but to compare the deterministic model version of the SAMGODS with the stochastic model presented in this paper, it is best to use a linear cost specification, since the former uses linear costs.

The variable for inventory costs during road transport (transport time multiplied by value of the shipment) has the expected (negative) sign and is highly significant for most commodity groups. This variable captures time costs related to the capital cost of the inventory in transit and maybe also those related to deterioration and safety stock considerations. The time-dependent link-based transport costs (labour and vehicle costs) have already been taken into account in the transport costs. Estimation of the inventory cost variable for chains involving rail and sea did not lead to significant coefficients. This is probably due to the possibility that capital costs of an inventory in transit are most relevant for truck transport.

The access to rail/quay dummy variables was included in the utility functions of choice alternatives where rail/quay was used as the first or second mode in the chosen transport chain. The interpretation of the parameter values is that shippers located in the proximity of or access to rail track or quay yard are more likely to choose chains that start with a rail/quay leg (or use these modes on the second leg of the chain). The two dummies are, however, not significant for most commodity groups.

For most commodity groups, we find significant positive effects for the value density (the value of the shipment divided by its weight) variable. The relevant alternatives for this variable are transport chain alternatives involving the two smallest shipment size categories (0-50 kg and 51-200 kg). The positive sign, therefore, implies that high value products correlate with smaller shipment sizes, which might also imply frequent shipments. We also find that international shipments tend to be shipped more using chains that use rail, ferry or vessel. The transport chain-specific constants mostly have negative signs and are significant. This is expected given that trucking, the reference chain type, is preferred to the other modes for its flexibility and ease of access (which are not included as explanatory factors in the models since they are not measured in the CFS).

3 From Deterministic to Stochastic Logistics model

3.1.SAMGODS review

The Swedish national freight transport model- SAMGODS- is one of the models that applies the aggregate-disaggregate-aggregate (ADA) framework (see: de Jong and Ben-Akiva, 2007; Ben-Akiva and de Jong, 2013).[11] The ADA model framework starts with an aggregate model for the determination of flows of goods between production (P) zones and consumption (C) zones (being retail for final consumption; and further processing of goods for intermediate consumption). The PC flows are derived from a gravity-type model. After the determination of these PC flows, comes a disaggregate “logistics” model, that on the basis of PC flows produces OD (origin-destination) flows for network assignment. A PC flow that uses the transport chain road-sea-road between the production and consumption locations contributes to three OD flows (one for each of the modes in the chain).

The logistics model in turn consists of three steps:

A. Disaggregation of zone-to-zone flows to individual firms at the P and C end;
B. Models for the logistics decisions by the firms (shipment size, trans-shipment locations and modes in a transport chain); This gives OD flows at the level of the annual firm-to-firm flows;
C. Aggregation of the information per shipment to zone-to-zone OD flows for network assignment.

[11] Akin to de Jong and Ben-Akiva (2007) a recent study by Zhao et al (2015) a freight temporal assignment model where disaggregate methods are used to assign aggregate annual flows to aggregate daily flows. We note there are other approaches to simulating freight flows at the national or broad regional levels using log-linear, micro-simulation, agent-based and direct-demand modeling efforts in various countries which are compehansively review by Chow et al (2010).

This model structure allows for logistics choices to be modelled at the level of the decision-maker. The network assignment is an aggregate model and is represented by the last A in ADA.

When the logistics model within the ADA-framework for Sweden (and Norway) was first conceived, the idea was that the logistics model would be estimated on data at individual shipment level from the Swedish CFS (see de Jong and Ben-Akiva, 2007, section 7). Since the deterministic logistics module as such is complex and the estimation of disaggregate models would take a significant amount of time, a 'preliminary' or 'prototype' version of the logistics model was developed in both Sweden and Norway (see de Jong and Ben-Akiva, 2007, section 8) in 2005/2006. This version did not require disaggregate estimation. Instead it relied on a cost minimisation per firm-to-firm (f2f) flow, where for each f2f flow only one alternative (namely the one with the lowest total logistics cost) is chosen. Because it uses different transport solutions for different firm sizes and shipment sizes, the all-or-nothing character of the deterministic model is reduced.

After the prototype had been developed, it has been improved in a number of rounds and also calibrated to aggregate data for a base year, but the current official version of the SAMGODS logistics model still uses a deterministic logistics model. The same holds for the other ADA models developed so far. A partial exception is that the Danish national freight model contains a module for the choice of mode to cross the Fehmarn Belt screenline that uses a random utility model estimated on disaggregate data (including stated preference SP surveys in the Fehmarn Belt corridor). Other transport chains, however, for example in Denmark, are handled by a deterministic logistics model (Ben-Akiva and de Jong, 2013, section 4.6). And also in Norway estimations have taken place recently on disaggregate data for the flows between Norway and Sweden from the Swedish CFS.

3.2. Stochastic Model procedure

We programmed a prototype stochastic logistics model for Sweden based on the estimated transport chain and shipment size models for two commodities: metal products and chemical products.

The stochastic logistics model was estimated on shipments from the CFS 2004-2005. In the implementation we do not use the CFS records directly, but we apply the estimated transport chain and shipment size models from Section 2 to the annual firm-to-firm (f2f) flows that are also used in the current deterministic logistics model. These f2f flows are taken from the first step of the logistics model (step A: disaggregation; see Section 3.1), which remained the same in this prototype For every f2f flow within a commodity group, the new prototype stochastic logistics model now predicts the choice of transport chain and shipment size and it does so by producing choice probabilities for every available alternative.

During the application of the stochastic logistics model the following steps are performed:

a) *Determine the longlist of transport chains.* This step fully corresponds to the corresponding step in the deterministic model. Transport chains with optimal transshipment locations are determined for each of the chain types distinguished within the deterministic model. For these chains, transport distance and time are calculated. Unimodal Level of Service matrices are read in for all possible chain leg modes. Then optimal chains are constructed using a one-to-many algorithm that follows a stepwise approach in adding extra legs to chains and determining the optimal transfer locations (Significance, 2015). Since we do not observe the transhipment locations in the CFS, we could not include this choice in estimation. Therefore, in the stochastic prototype, the determination of the optimal transhipment locations for each available chain type from the set of available locations is still done deterministically.

b) *Reduce the number of chain types to the more limited set (shortlist) distinguished in the stochastic model by a deterministic choice amongst similar chain types.* Within the deterministic model several rail modes (container train, feeder train, wagonload train, system train) and sea modes (direct sea, feeder vessel, long-haul vessel) are available. On the other hand, within the stochastic model only one rail and one sea mode are distinguished (due to the classification used in the CFS). To select the rail and sea modes to be used in the stochastic model, as well as to determine the vehicle types to be used on each leg, we still apply the deterministic model. This has to be done for all of the available weight class (as shown in Table 1) choice options separately. After step (b) the best chains and vehicle types are available for the choice set of chain types and weight classes used within in the stochastic model:

Chain types:

Truck

Vessel

Rail

Truck-Vessel

Rail-Vessel

Truck-Truck-Truck

Truck-Rail-Truck

Truck-Ferry-Truck

Truck-Vessel-Truck

Truck-Air-Truck

Truck-Ferry-Rail-Truck

Truck-Rail-Ferry-truck

Truck-Vessel-Rail-Truck

Truck-Rail-Vessel-Truck

However, not all the above choice options will be available for each commodity. As an example, Figure 2 shows the combinations of transport chain type and weight class that are available in the stochastic model for commodity metal products (based on the actual frequencies in the CFS 2004-2005).

c) *Calculate the utilities for each of the choice options in the stochastic model.* In step (b) the number of available chain types has been reduced to at most 14 the maximum number of chain types distinguished within the stochastic model. Within the third step the utility functions are calculated for each of the available choice options (combinations of transport chain and shipment size) given above. The estimated coefficients are multiplied with the relevant chain input values obtained from the chains determined in step (b). In this step there is no information available on the value of goods (expressed in SEK) or the value density (expressed in SEK/kg) on specific firm-to-firm relations. Therefore the average commodity value is used in application of the model. The dummy coefficient for direct rail access is always applied to PC chains consisting of a single rail leg and never for the other chains. Quay access is not used in the implemented models for metal and chemical products.

d) *Calculation of the choice probabilities.* When the utilities have been calculated for all available transport chain types and weight classes, the probability for each choice option can be calculated in the usual way for multinomial logit models.

e) *Aggregation of flows.* Similar to the deterministic model, all firm to firm flows are aggregated to obtain OD-flows. However, instead of the single best chain generated by the deterministic model, we now aggregate over all choice options and weight each choice option with the probability calculated in step (d).

3.3 Calibration procedure for the stochastic model

The stochastic logistics model described above includes alternative-specific constants for all transport chain alternatives (minus one). This means that the model will reproduce the market shares (in terms of the number of shipments) for the chains as they are in the estimation data (which is based on the CFS, but also depends on the question whether we have level-of-service data for a particular transport chain and PC relation) in the current deterministic logistics model. This is not necessarily a good reflection of the actual importance of the various modes for the commodity involved. We also have observed aggregate data on the tonne-kilometers by mode from transport statistics). For metal products and chemical products these numbers for the year 2006 are in the columns labelled 'statistics' in Table 4.

When we compare the tonne-km by mode (by OD-leg, so also access/egress tonne-km are counted) from the uncalibrated stochastic model to these observations, we see that it overestimates the road and the sea tonne-km for both products. For metal products there is some underestimation of rail, and for chemical products the stochastic model predicts a very limited (less than one million tonne-km) use of rail transport. This is in line with the CFS, but not with the calibration data (where rail has a market share of more than 10% for chemical products). The deterministic logistics model (without the rail capacity module) on the other hand overestimates the observed rail tonne-km.

To calibrate the stochastic logistics model, we use the observed tonne-km shares as targets and add to each transport chain alternative constant in the utility functions of the stochastic model:

Ln (O_j/M_j)

In which:

O_j: observed share of mode j

M_j: Modelled share of mode j

This makes under-predicted modes more attractive and over-predicted ones less attractive. To reach the observed targets, this procedure needs to be repeated several times; it is an iterative calibration procedure. For the comparison of elasticities in this report we performed a limited number of iterations with the stochastic model for both metal products and chemical products, which brought us much closer to the observed targets, but still not very near.

4 Deterministic vs. Stochastic, a comparison using two commodity groups

4.1 Method

The stochastic approach applied in this paper for different commodities is intended to be a substitute or complement to the deterministic model, which currently constitutes the very heart of the logistics model in the SAMGODS model system. For metal products and chemical products, both the deterministic and the stochastic model have been implemented into an executable. By switching these executables when running the SAMGODS model system, we may conveniently switch between the deterministic and the stochastic models. Both models operate on the same set of input data when it comes to demand matrices and costs for 2006.

All results in this section have been obtained using the base scenario, Base2006, of SAMGODS version 1.0 (April 2015). This scenario has been run without taking into account railway capacity restrictions. Since the scenario was originally calibrated using the Rail Capacity Management module, model output may significantly deviate from statistics. For example, the total rail tonne-km is much larger in model output than in transport statistics.

The results in terms of tonne-km per mode presented in Table 4 are derived from the direct output from the deterministic and stochastic logistics model. These are less precise than those from the corresponding assigned quantities, and introduces extra uncertainty in the results, in particular when it comes to computed tonne-km within Swedish territory.

4.2 Comparison of model prediction on selected output measures

In the first step we checked the outcome of the model runs against the statistics. Table 3 below shows that both the deterministic and the stochastic model overestimate the tonne-km in Sweden a lot. Another observation that can be made is that the deterministic model calculates relatively high shares for rail while the stochastic model calculates relatively high shares for road and sea. Both the overestimation of the total tonne-km and the deviation from the modal split in the statistics will have consequences for the calculation of the elasticities.

4.3 Comparison of elasticities

Of major interest is to compare the model's responses to small (or larger) perturbations in input data, i.e. elasticities. The logistics model comprises large sets of both input and output data. Only a few elasticities are presented here (and one has to take into account that the total demand per commodity is constant). Our choice has been to vary, on the input side, the link costs that includes the distance and time based costs for all vehicle types within road, rail and sea and on the output side, tonne-km in Sweden.[12] In Table 5 we summarize the scenarios investigated.

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[12] Tonne-km in Sweden is the sum of the domestic transports and the domestic parts of international transports that are carried out in Sweden.

Results for metal products

In Table 6, results for change in tonne-km in Sweden are shown for the different scenarios, computed with the deterministic and the stochastic model. We make the following observations:

- All own-price elasticities have the expected sign.
- The own elasticities for changes in road and rail cost are in all cases smaller in the stochastic model than in the deterministic model. This is in line with our expectations: we expected that the inclusion of other factors than costs in the stochastic model and the move away from the all-or-nothing choice in the deterministic model would reduce the modal shifts (that are calculated for the deterministic model). Especially for road cost changes, the stochastic model elasticities are more plausible (e.g. they do not become as strong as -2.87 as in the deterministic model). For changes in the sea transport cost, some elasticities are stronger in the deterministic model and some in the stochastic model. The elasticities can differ substantially between cost increases and decreases (in a logit model elasticities for increases and decreases do not have to be the same, this depends on where the starting point is located on the S-shaped logit curve).
- Nearly all cross price elasticities have also the opposite sign of the direct elasticity, which is what one should expect from a model in which the modes would be mutually exclusive ('competing') alternatives. However, both the deterministic and the stochastic model have transport chains in which several modes are combined (e.g. with rail as main haul mode and road for access and egress). As a result, increasing the cost of rail transport could lead not only to an increased share of the truck only chain (competition), but also to a reduced truck use in the truck-rail-truck chain (complementarity)[13]. This usually refers to rather short road access and egress distances, but still it reduces the elasticities (in absolute values) and can even lead to cross elasticities with the same sign as the own-price elasticities. Most of the shifts (in both models, especially in the stochastic model) are from/to the land based modes to/from sea.
- Transfers to/from rail are very small in the stochastic model. This could imply that current rail shippers are captive to the mode to some extent (note that metal products is characterized by the dominance of one big shipper). On the other hand, it could also imply

[13] Furthermore, there can also be changes in shipment size in both models as a result of cost changes.

that other modes are competitively priced to rail, implying that larger price incentive or availability of infrastructure is needed to attract more shippers to rail.

Results for chemical products

In Table 7, results for change in tonne-km in Sweden are shown for the different scenarios, computed with the deterministic and stochastic model. The following conclusions can be drawn from this:

- In all cases, the own-price elasticities have the expected sign.
- As expected, the own elasticities for changes in road, rail and sea transport cost are smaller in the stochastic model than in the deterministic model. For all these three cost changes, the elasticities of the stochastic model seem more plausible (the deterministic model has elasticities here that go beyond -2). Again, there are substantial differences between cost increases and decreases.
- In most cases the cross price elasticities have also the opposite sign as the own elasticity. For the stochastic model, this is always the case, but for the deterministic model, there are stronger complementarities between modes.
- Large differences in modal split in the base (see Table 3) lead to very different elasticities.
- Transfers from road to rail (in the stochastic model) are higher for chemical products than for metal products. Also the own elasticity of rail costs is stronger for chemical products than for metal products. This is all probably due to the lower share of rail transport for chemical product shippers compared to metal product shippers. Given this low share of rail in chemical product shipments, any price incentive will attract shippers to shift to rail.
- For chemical products, sea transport has a higher share than for metal products. This is reflected in the elasticities of the stochastic model which yields stronger sea cost elasticities in the model for metal products than for chemical products.

Overall results

Elasticities differ according to commodities, regions (modal split etc.), distance class, modelling approaches and measures (tonne, tonne-km, vehicle-km), see e.g. de Jong et al. (2010). This source does not contain recommendations per commodity type. For all commodities the recommended road tonne-km price elasticity on the number of tonne-km by road through mode choice in de Jong et al. (2010) is -0.4 and the lower bound provided is -1.3. Some of the road costs elasticities of the deterministic model for metal and chemical products are clearly beyond this lower bound. The own elasticities, measured in tonnes, calculated using a weighted logit mode-choice model for the Öresund region (Rich, Holmblad & Hansen (2009) are in about the same range as the own elasticities measured in tonne-km from the stochastic logistics model calculated in this paper.

5 Conclusions and ideas for further research

This paper has presented a new stochastic model of transport chain and shipment size choice which overcomes a well-known disadvantage of deterministic models that lead to implausibly large responses as a result of changes in scenario variables. For estimation of choice models, we used the Swedish Commodity Flow Survey (CFS) from 2004/2005. Parameter estimates from this model were then used for estimation of a full random utility, i.e. stochastic, logistics model.

We have setup a stochastic logistic model for two commodity groups, metal products and chemical products. Although the stochastic model is implemented for the two commodities, we have estimated multinomial logit models for 14 commodities for which a stochastic model could be implemented in the future. We compared transport cost and time elasticities for tonne-km between the stochastic and deterministic models for the two commodities, which has not been done before for such models. These elasticities differ between the two models, they are usually smaller in the stochastic model, confirming that the problem of potentially large demand responses (overshooting) is solved or at least reduced in the stochastic logistics model.

In future endeavors, the difference between the two models could be further studied by looking at elasticities on other output measures such as vehicle-kilometer. Similar models can be estimated on the Swedish CFS 2009, the CFS 2016 that will be available in the end of 2017, the French ECHO data, the US CFS and hopefully also on future surveys of this kind in other countries. In estimating such models, other costs specifications (logarithmic, linear and logarithmic, splines) as well as more flexible substitution patterns between alternatives (e.g. nested logit, mixed logit) could be tested.

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