EJTIR

Issue 16(4), 2016
pp. 619-632
ISSN: 1567-7141
tlo.tbm.tudelft.nl/ejtir

Analyzing model uncertainty and economies of scale of the Swedish national freight model to changes in transport demand

Jonas Westin[1]
Centre for Regional Science, Umeå University and Centre for Transport Studies (CTS), KTH Royal Institute of Technology, Sweden.

Inge Vierth[2]
Swedish National Road and Transport Research Institute (VTI) and CTS, Sweden.

Gerard de Jong[3]
Significance, The Hague, The Netherlands, Institute for Transport Studies, University of Leeds, United Kingdom and CTS, Sweden.

Rune Karlsson[4]
VTI and CTS, Sweden.

Niclas A. Krüger[5]
School of Business, Örebro University and VTI, Sweden.

Magnus Johansson[6]
Transport Analysis and Sweden and CTS, Sweden.

The purpose of the paper is to analyze model uncertainty and economies of scale of the Swedish national freight transport model system Samgods to changes in its zone-to-zone base matrices. Even though economies of scale is important for freight transport, few studies analyze model uncertainty and economies of scale at a national level. Compared to many large scale network-based freight models working on aggregated transport flows, an important feature in Samgods is that it simulates logistics behavior at a disaggregated firm level. The paper studies effects on total tonne- and vehicle-kilometre, modal split, consolidation and logistics costs when the base matrices are scaled up and down and estimates economies of scale for Swedish freight transports. The results indicate that the logistics model can find new logistics solutions for larger demand volumes, mainly by shifting freight to sea transport. If transport volume increases with one percent, average logistics cost per tonne is reduced by around 0.5 percent. Part of the cost reduction comes from increased consolidation of shipments due to larger transport volumes. The results derived in the paper can serve as a reference for empirical validation and comparisons with other large scale freight models. The paper is a first contribution that tries to fill the knowledge gap on the impact of base matrices on transport model outcomes, such as economies of scale, in the context of a full-fledged real-world freight transport model.

Keywords: *large scale freight model, model uncertainty, economies of scale, sensitivity, base matrices.*

[1] A: Samhällsvetarhuset, Umeå University, 90187 Umeå, Sweden T: +46 907 865 155 E: jonas.westin@umu.se
[2] A: Teknikringen 10, 11428 Stockholm, Sweden T: +46 855 577 032 E: inge.vierth@vti.se
[3] A: Koninginnegracht 23, 2514 AB, The Hague, The Netherlands, T: +31703121531, E: dejong@significance.nl
[4] A: Olaus Magnus v. 35, 58330 Linköping, Sweden T: +46 13 204 135 E: rune.karlsson@vti.se
[5] A: Fakultetsgatan 1, 70182 Örebro, Sweden T: +46 19 303 000 E: niclas.kruger@oru.se
[6] A: Torsgatan 30, 11321 Stockholm, Sweden T: +46 104 144 215 E: magnus.johansson@trafa.se

1. Introduction

There is a trend in freight transport to use larger and larger vehicles and vessels to exploit economies of scale. Time series from Sweden reveal higher increases for tonne-kilometres than for vehicle- and vessel-kilometres for road, rail and sea during the last decades (Transport Analysis, 2016).[7] This development needs to be taken into account in transport planning since it influences the requirements on the transport infrastructure. Political efforts to use a few major freight corridors strengthen the use of larger trucks, trains and vessels. Policies aiming at a more efficient use of the transport system, like the differentiation of rail track fees, the introduction of road tolls or the revisions of regulations regarding vehicle dimensions, also give incentives to exploit economies of scale.

Since the recession 2008/2009 freight transport demand has recovered and further growth is forecasted at both national and international level. When modelling freight transport, it is therefore important to capture the impact of increased or decreased transport demand on the choice of vehicle/vessel sizes within and across the modes. These choices influence shippers' logistics costs, comprising transport costs, order costs and inventory costs. Shippers need to consider the trade-off between transport costs on the one side and inventory costs and order costs on the other side. Typically, it is necessary to consolidate goods from different shippers to fill whole vessels, trains and trucks.

The paper analyzes the sensitivity of the Swedish national freight model system Samgods to changes to one of its main input variables, the base matrices, and uses this to calculate an estimate of the economies of scale for freight transports in, to and from Sweden at an aggregate level. Samgods is one of few national freight model systems that simulates logistics decision at a disaggregated firm level (de Jong et al., 2013). Since responses to demand changes in this model are non-linear, the effects of increased or decreased demand on the economies of scale can be important, both per se and in combination with policy measures. The model comprises three sub modules: (i) base matrices that describe annual transport demand per commodity at the zone-to-zone and firm-to-firm level, (ii) a deterministic logistics module that minimizes shippers' annual logistics costs and (iii) a network model that distributes the selected transport chains over the transport infrastructure. Given a fixed annual transport volume for each firm-to-firm relationship the choice of shipment size, transport chains, transfer locations, consolidation levels and vehicle/vessel sizes for each leg in the transport chain are modelled (Ben-Akiva and de Jong, 2013).

The results derived in this paper can serve as a reference for empirical follow ups and comparisons to other large scale freight models. Results can hopefully be used in other aggregated-disaggregated-aggregated models of the same type, e.g. the Norwegian, Danish or Flemish model. The simulations can also be regarded as a test to find out whether this pioneering model behaves in a plausible way when its base year matrices are changed.

1.1 Purpose and structure of the paper

The purpose of the paper is to analyze model uncertainty and economies of scale of the logistics model in the Swedish national freight transport model system Samgods to changes in its zone-to-zone matrices. RAND Europe (2005) and de Jong et al. (2007) distinguish between two reasons for uncertainty in the transport model outputs; 'input uncertainty' and 'model uncertainty'. Investigating the sensitivity of logistics model outputs to changes in the zone-to-zone matrices is a special form of uncertainty analysis of input variables. Instead of a single input value, the matrices contain a very large number of values that refer to a base year or some future year. Two motivations for the uncertainty analysis are to improve the assessment of the impact of different

[7] Inland waterway transports hardly exist in Sweden and air freight is not addressed in the paper. The annual transported volumes in tonnes for air freight is also very limited compared to the other modes.

policies when economies of scale effects are present and to serve as a basis for further model development of disaggregated non-linear freight model systems.

Many models, both in passenger and freight transport, use base matrices to describe transport demand. These matrices are often estimated using models and are hence uncertain. However, little is known about the impact of this uncertainty in base matrices on the final model outcomes. Uncertainty in passenger model outcomes has been studied for various sources of uncertainty, such as parameter uncertainty or uncertainty in the model's input variables such as transport costs and income (e.g. de Jong et al., 2007, Manzo, 2014). These effects can be substantial (Zhao and Kockelman, 2002) and there is no guarantee that the impact of the base matrix will be smaller. The paper is a first contribution that tries to fill the knowledge gap on the impact of base matrices on transport model outcomes, such as economies of scale, and moreover does so in the context of a full-fledged real-world freight transport model.

The paper analyzes how sensitive the model outputs are to changes in total transport demand by studying the effect on total tonne-kilometre and vehicle/vessel-kilometre per mode, modal split, consolidation levels and logistics costs when the zone-to-zone-matrices are scaled up and down. The paper also calculates estimates of the aggregate economies of scale, for the full model and per commodity, for the freight transports in, to and from Sweden.

Section 2 provides a review of the use of uncertainty analysis in transport modelling. Section 3 discusses the existence of economies of scale in the Swedish transport system. Section 4 contains a brief description to the Samgods model system. Section 5 presents results from the simulations in terms of e.g. number of tonne-kilometres and vehicle-kilometres by mode, modal split and logistics costs together with an estimation of the economies of scale in the model. Section 6 concludes.

2. Uncertainty analysis in transport modelling

Uncertainty analysis can be used in transport modelling to obtain uncertainty margins or confidence intervals for model outputs. Instead of making predictions in the form of central values (point estimates) for some model output variables, policy-makers may want to have uncertainty margins (e.g. 95 % confidence intervals) for the variables. This makes it possible to select robust policy measures: measures that have desired consequences for likely outcomes of variables.

2.1 Methods for analyzing uncertainty in transport models

RAND Europe (2005) and de Jong et al. (2007) distinguish between two reasons for uncertainty in transport model outputs; 'input uncertainty' and 'model uncertainty'. In Monte Carlo simulations with the Dutch National and Regional passenger transport models by these authors, input uncertainty (e.g. changes in car ownership levels or future incomes) was clearly more important for the uncertainty in the model outputs than model uncertainty (e.g. confidence intervals around estimated parameters). In this setting model uncertainty can both refer to uncertainty in the parameter values of the model and to changes in the structure of the transport model itself through changes in the model specification. For instance, by using different functional forms (e.g. linear versus log-linear or Box-Cox), a different selection of model variables or by including more complex model behavior and feedback loops (e.g. Næss et al., 2012).

Methods for analyzing how sensitive a model is to uncertainty can be divided into two categories; methods where uncertainty in a single variable or parameter is analyzed at a time and methods where uncertainty in multiple variables or parameters are analyzed simultaneously. Uncertainty in a single variable or parameter can often be expressed in the form of an elasticity that measures the effect on an output variable from a change in a single input. One can either change autonomous variables such as GDP or the oil price, to find out how large the influence of the external environment is on the variables of interest, or change policy variables, such as the fuel tax, to simulate the impact of potential policy measures. The most common procedure for analyzing the effect of varying multiple variables or parameters together is scenario analysis. A more uncommon method is a systematic Monte Carlo simulation that can produce uncertainty margins or confidence intervals for the model outputs on the basis of uncertainty margins in the input variables or model parameters.

Investigating the sensitivity of logistics model outputs to changes in the base matrices is a special form of sensitivity analysis of input variables. Instead of a single input value, the base matrices contain a very large number of values. Since the estimation of the matrices are influenced by different kinds of measurement and matrix modelling errors, their uncertainty is multidimensional.

Scenario analysis

Scenario analysis was pioneered by Shell and RAND Corporation in the early seventies to investigate the impact that the combined effect of the main external forces can have on the outcomes of interest. A scenario is a consistent picture of a possible future. It consists of a number of assumptions on the values of input variables that are all part of an overall view of how a system may develop (e.g. a scenario for a situation of increased protectionism versus a scenario of free trade; a green scenario versus an economy-first scenario).

The key to scenario building is determining which external influencing factors are most important for the outcomes of interest (such as tonne-kilometer by mode, or emissions) and which levels these variables might take in a possible future. Only factors that are likely to change and for which changes are likely to have a large influence on the outcomes of interest need to be included in a scenario. To make the scenarios internally consistent, the scenarios need to take into account that several influencing factors can be correlated over time (so for instance a scenario with a high income growth will also have a high consumption). A method that can be used to structure and analyze consistent scenarios is Morphological Analysis, see Eriksson and Ritchey (2002).

Scenario analysis has been used in very diverse fields, including energy policy, military strategy-making and economics. In transport research, it has been used in many countries, either building on general-purpose scenarios (e.g. the Dutch WLO scenarios, CPB et al., 2006), or constructing scenarios specifically for the transport sector, such as the STEPs (Fiorello et al., 2006) and the TRANSVISION (Petersen et al., 2009) scenarios for Europe.

An important element of a scenario analysis is the idea that various scenarios should be tested: a model should be run for at least two, but preferably more possible future states of the world. Scenario studies usually cover between two and five scenarios. If possible, the set of different scenarios tested in a study should cover most of the likely variation in the influencing factors. However, probabilities are in general not attached to the various scenarios: there is no indication that one scenario is more likely than another, or that all are equally likely. This makes it impossible to derive uncertainty margins for the output variables from scenario analysis. Policy-makers sometimes have revealed a tendency to focus on a 'middle' scenario (e.g. when there are three scenarios in terms of economic growth: low, medium and high growth), but this is not in line with the general idea of scenario analysis.

Monte Carlo simulation

The use of Monte Carlo simulation in the application of transport models means that numbers are drawn from a statistical distribution, such as the normal or uniform distribution, and that the model is run repeatedly for each set of numbers. One might draw random numbers both for input variables and for model parameters. The outcomes of the various runs may be summarized, using the mean for some model outcome and the standard deviation. To get stable results one needs (depending on the application) at least several dozens of runs, but hundreds or thousands is not exceptional depending on the complexity and running time of the model. Because the selection of input variables (or of model parameters) is done from a known (assumed) distribution, confidence intervals for the model outputs can be calculated. An advantage of the method is that the model output distribution can be estimated based on a large number of simulation runs.

In RAND Europe (2005), de Jong et al. (2007), Rasouli and Timmermans (2012) and Manzo (2014) reviews are provided of studies in transport that have provided uncertainty margins for transport model outputs. For finding a confidence interval for model outputs that is due to variation in the model parameters there is a wider variety of methods. Most of these studies have used Monte Carlo simulation. Besides Monte Carlo simulation, some studies use the analytic expression of the variance of the model output as a function of the variances of the model parameters. This is only a feasible alternative if the model is relatively simple (and if proper variances for the parameter estimates are available from the estimation process). Examples of the use of the analytic method can be found in Ben-Akiva and Lerman (1985) and Daly et al. (2012). The method selected for the application to the Dutch national and regional passenger transport models in RAND Europe (2005) and de Jong et al. (2007) was also Monte Carlo simulation for both inputs and parameters.

The difficult issue in the application of Monte Carlo simulation is how to determine the distribution to draw from and its means, variances and co-variances. Ideally one would want to use a multivariate distribution containing all important input variables (and/or model parameters). In practice, most studies use univariate distributions and assume that the different influencing variables are independent (no correlations) or that the correlation structure is very simple (e.g. by grouping variables into perfectly correlated subsets), see for example the analysis in Westin and Kågeson (2012). A common method for risk analysis is to take the likely total range of variation of an input variable (based on the past variation) and to assume a symmetric triangular distribution that covers this range. Other studies use multivariate normal distributions taking account of correlation between input variables (or parameters). The variance-covariance matrix of the model parameters can come from the model estimation (though for proper estimation, it may be necessary to use resampling methods, such as Jackknife or Bootstrap).

A Swedish application of Monte Carlo methods used in transport modelling is Beser Hugosson (2005) who uses a Bootstrap method to find confidence intervals for total demand, car demand on specific OD relations, flows on specific road links and railway lines and values of time for the Swedish national passenger transport model (SAMPERS). Another question is whether there will be propagation of errors: especially when a number of models are used sequentially, errors in the inputs can lead to bigger errors in the model outputs (reinforcing initial deviations), but also to smaller output errors (equilibrium mechanisms), e.g. see Zhao and Kockelman (2002).

Comparison of forecasts and outturns

A number of studies has been looking at the issue of actual versus predicted outputs. Flyvbjerg et al. (2006) have found evidence of optimism bias (the mean of the model forecasts is significantly higher than the mean outturn) for public transport projects, but not for toll-free road projects. Bain (2009) did find optimism bias for privately financed toll road projects. For both road and public transport projects, large differences between model predictions and outturns were found. These error margins can often be larger than what transportation planning professions would expect (see Bain, 2011), and sometimes also larger than the predicted confidence intervals that take both model and input uncertainty into account. Even the most complete studies on uncertainty margins apparently do not fully include all sources of error. From a compilation of

Swedish passenger and freight transport forecasts between 1975 and 2005; one conclusion is it has been difficult to predict deviations from historical trends (Vierth, 2005).

3. Economies of scale in the Swedish transport system

Table 1 shows time series over tonne-kilometre, vehicle/vessel-kilometre and tonnes per vehicle/vessel for rail, road and sea transports in Sweden. The fact that the number of transported tonnes per truck, per freight train and per vessel increase over time shows empirical evidence for the existence of economies of scale for all transport modes in the Swedish transport system.[8] The figures for road transports need to be interpreted with caution due to uncertainties for the calculation of the tonne-kilometres by foreign vehicles in Sweden. Different developments, e.g. the use of heavier trains to transport of heavy goods versus the increased use of container trains to transport light and bulky goods, cancel out each other. For the time being, there is also not enough statistical data to carry out an in-depth analysis at the commodity level.

Table 1. Table 1. Index of tonne-km, vehicle-km and tonnes per vehicle for road and rail transports and tonne-km, tonnes loaded/unloaded, port calls and tonnes per call for sea transports in Sweden

	2006	2007	2008	2009	2010	2011	2012	2013	2014
Road: Tonne-km	100	103	105	110	91	94	96	106	109
Road: Vehicle-km	100	105	105	98	100	103	99	97	100
Road: Tonnes per lorry	100	99	100	112	91	91	96	109	109
Rail: Tonne-km	100	104	103	92	105	103	99	94	96
Rail: Train-km	100	102	96	86	87	91	83	80	79
Rail: Tonnes per train	100	103	107	106	120	112	119	118	122
Sea: Tonne-km	100	101	88	98	98	95	88	94	94
Sea: Tonnes loaded/unloaded	100	102	104	90	100	97	96	93	94
Sea: Port calls	100	101	101	100	93	93	88	84	84
Sea: Tonnes per call	100	100	103	90	107	104	109	111	112

Sources: Transport Analysis (Trafikanalys), Swedish Transport Administration (Trafikverket), Swedish Maritime Administration (Sjöfartsverket).

Logistics costs (comprising transport costs, order costs and inventory costs) are all important components in the shippers' choice of transport alternatives. However, due to lack of cost data for all single firms and relations it is difficult to empirically estimate the cost components and the economies of scales. Nevertheless, it is obvious that shippers, forwarders and carriers try to consolidate and use larger vehicles and vessels to lower their transport costs. But typically, certain frequencies need to be maintained when it comes to deliveries and reduced transport costs need to be balanced against increased inventory and order costs. This is taken into account in Samgods' disaggregated logistics model.

4. The Swedish national freight model system Samgods

The Swedish National Freight Model System Samgods is a deterministic freight model that calculates annual transport flows in Sweden based on cost minimization. Compared to many large scale network-based freight models working on aggregated transport flows, an important feature in the Samgods model is that it contains a logistics module that simulates logistics behavior at a disaggregated firm level. The model framework consists of base matrices that

[8] It is unfortunately not possible to present longer time series for all three modes.

describe transport demand, a deterministic logistics model that minimizes the shippers' annual logistics costs and a network model that distributes the selected transport chains over the transport infrastructure. The three sub modules of the Samgods model system are described below.

(i) Transport demand is described in 34 fixed commodity-specific zone-to-zone production-consumption matrices (PC-matrices) for 464 zones (290 municipalities in Sweden and 174 larger administrative regions outside Sweden). The PC-matrices contain data on the total annual transport volumes in tonnes between producers in one zone to consumers in another zone divided by commodity type. The PC-matrices are estimated using data from regional accounts, input-output tables, foreign trade statistics, the Swedish Commodity Flow Survey (CFS) as well as different models, i.e. gravity models (Edwards et al., 2008; Edwards, 2008). The zone-to-zone flows are disaggregated into firm-to-firm flows, assuming transports between small, medium and large firms and very large specific singular flows. Due to limited information on regional transport demand, it is very difficult to validate the PC-matrices, at the firm-to-firm or zone-to-zone level as such. Transport and traffic forecasts are however calculated in the model and can to some extent be validated for the base year.

(ii) The logistics model has an ADA-structure (Aggregated-Disaggregated-Aggregated) where the aggregated PC-matrices first are disaggregated from zonal PC-flows to annual firm to firm flows as illustrated in Figure 1. The logistic decisions in the model are taken at the disaggregated level. In the last step, the shipments are aggregated back to origin-destination-flows (OD-flows) of loaded and empty vehicles and transported tonnes in the transport network.

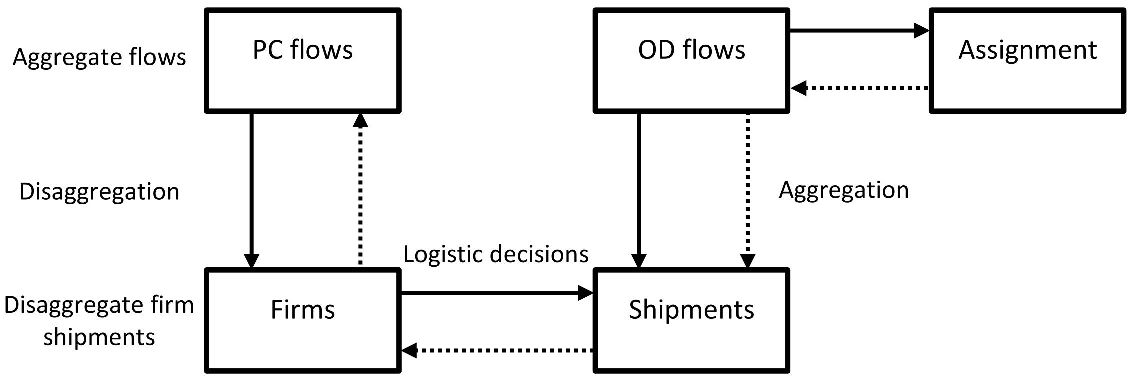

Figure 1. ADA structure of the national freight transport model system (de Jong et al., 2011)

Within the logistics model, the firms' annual total logistics costs are minimized. The cost minimization is a trade-off between transport costs, order costs and holding costs. The logistics model also takes into account that transport costs per unit can be reduced by using larger vehicle types when transporting goods from one or several shippers. The choice between container and non-container transport chains is also modelled. By combining predefined transport costs *per vehicle kilometre* with within the model calculated load factors, transport costs *per tonne-kilometre* are calculated. Based on these inputs the model determines the shippers' choice from a set of constructed transport chains. Logistics costs per tonne are calculated. It is assumed that the transport companies pass all cost changes to the shippers.

The logistics model contains 33 vehicle types: five road vehicle types with 2 to 47 tonnes loading capacity), eight rail vehicle types with 450 to 6,000 tonnes loading capacity), 19 sea vehicle types with 950 to 250,000 tonnes loading capacity), and one air.[9] For sea transports, different types of

[9] The number of vehicle types has been increased in later model versions.

vessels (container, ro-ro and other vessels) and ferries are included. Different vehicle sizes allow for the modelling of economies of scale. This aspect is especially important for vessels that differ significantly in size (and therefore costs). The capacity of the vessels varies from 1 000 to 250 000 dwt. Transport costs are divided into underway costs and transfer costs. The underway costs are in turn divided into time-based costs, distance-based costs and infrastructure fees such as fairway dues and pilot fees.

Only consolidation within the 34 commodities is modelled, i.e. consolidation across commodities is not modelled. Consolidation is assumed to take place at terminals and not along the route (e.g. trucks picking up goods during the trip or vessels calling several ports during a trip) is not modelled either. These failures can indicate that the level of consolidation is underestimated.

(iii) The network model distributes the selected transport chains over the transport infrastructure. It takes into account infrastructure restrictions in form of maximum depth for vessels and maximum weight for trucks and trains. One relevant question in conjunction with transport policies aiming at the exploitation of economies of scale is which vehicle dimension (e.g. length, weight of trains and trucks) that is the limiting factor for the transported goods. Capacity restrictions in terms of number of trains per track, capacity restrictions in ports and road congestion are not included in the model version used in this paper.[10]

The analyses in the paper are made in Samgods model version 2012-09-12 running on the Cube 6.0 interface. For an overview of the deterministic Samgods logistics model, see: de Jong and Ben-Akiva (2007), de Jong et al. (2011) and Vierth et al. (2009).

5. Model uncertainty and economies of scale in the Samgods model

The paper analyzes the model uncertainty and economies of scale in the Swedish freight model system Samgods to changes in its PC-matrices. The section starts with a description of the base scenario of the model in 5.1. The analysis continues in 5.2 with an analysis of the effect on tonne-kilometres and vehicle/vessel-kilometres per mode, modal split and consolidation levels when the PC-matrices are uniformly scaled up and down. Section 5.3 finally studies the effects on logistics costs and estimates the aggregated economies of scale effects for both the total model and for different commodities. In the experiment, all elements in the PC-matrices are scaled up and down with the same amount, from -20% to +20%. The commodity mix and regional distribution are assumed to be constant in the scaling process. The disaggregation from zone-to-zone flows to firm-to-firm flows is also kept constant.

5.1 Samgods base scenario

As a reference point, the PC-matrices for 2006 and tonne-kilometres for the different modes in the Samgods base scenario are used. The total number of tonne- kilometres and modal split in Sweden are shown in Table 2. It has to be stressed that these outputs from the Samgods model are not fully in line with observations from the official transport statistics for domestic and international transports on the Swedish territory since the official model is not fully calibrated.[11]

[10] In later model versions rail capacity is modelled using linear programming.
[11] Compared to measured transport flows for the base year, road transports are overestimated and rail and sea transports underestimated in the model.

Table 2. Freight flows in, to and from Sweden: Transport performance (1000 tonne-kilometer) and modal shares in percent in the base scenario

	Road	Rail	Sea	Total
Million tonne-kilometres in Sweden	52.649	22.183	45.699	120.531
Modal shares (percent)	43.7%	18.4%	37.9%	
Million Tonne-kilometres inside and outside Sweden	97.542	37.783	539.223	676.732[12]
Modal Shares (percent)	14.4%	5.6%	79.7%	

As a measure of the average consolidation levels, the average tonne per vehicle/vessel is calculated by dividing the total tonne-kilometres per mode with the total vehicle/vessel-kilometres per mode. In the base scenario, the average consolidation levels for all transports inside and outside Sweden are 6.7 tonne/vehicle for road transport, 315 tonne/train for rail transport and 635 tonne/vessel for sea transport. These values are lower than statistics and depends to some degree on how empty transports are handled.

The total logistics costs in the base scenario is around SEK 360,000 million per year.[13] The total cost is divided into three cost components; order cost, holding cost and transport cost as shown in Table 3.

Table 3. Cost components in the base scenario for freight flows inside and outside Sweden

	Total logistics cost	Cost share
Order cost (million SEK)	51 000	14%
Holding cost (million SEK)	107 300	30%
Transport cost (million SEK)	205 300	56%
Total cost (million SEK)	363 600	100%

5.2 Effects of a uniform scaling of the PC-matrices

We analyze five scenarios where the elements in the PC-matrices are scaled from -20% to +20% compared to the base scenario. The relative changes in tonne-kilometres and vehicle-kilometres (in percent) as a function of the change in total freight volumes are shown in Figure 2.

[12] The base scenario also has 2.184 million tonne-kilometer of international air freight transport corresponding to a modal share of 0.3 %. The model does not include air transport for domestic transport in Sweden.
[13] 1 Euro is around 9.5 SEK which implies that the total logistics cost in the base scenario is around 38 000 million Euros.

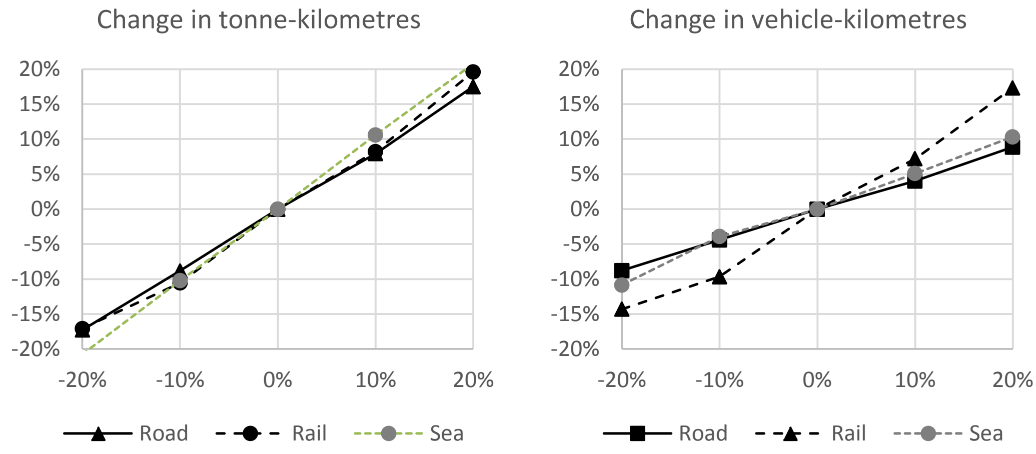

Figure 2. Change in tonne-kilometres and vehicle-kilometres (in percent) per mode inside and outside Sweden as a function of change in total transport volume

The figure reveals that the tonne-kilometres increases nearly linearly with transport demand. The change in vehicle-kilometres is however lower which implies that the average payload of the vehicles increases as a function of the total transport volume and the possibilities to use larger vehicles/vessels. Uncertainty in transport demand may therefore have a larger effect on tonne-kilometres than vehicle-kilometres. This can also be seen in Figure 3 where the average consolidation levels measured as tonne per vehicle for different modes is shown. The effect comes primarily from higher load factors for existing vehicles/vessels although the model also change to larger vehicles/vessels. The effect is strongest for sea transport where the shippers have more alternative vessels of different sizes to choose from when the freight volumes changes compared to road and rail operators.

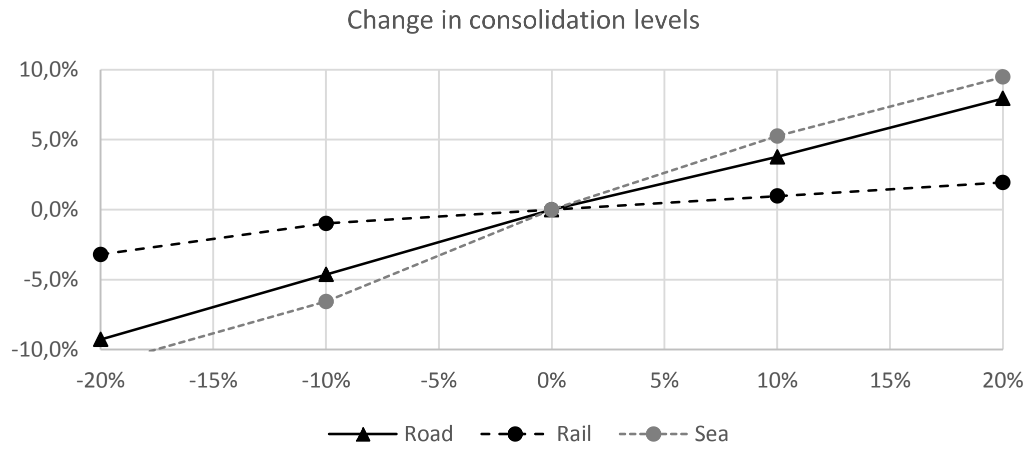

Figure 3. Change in average consolidation levels per mode in, to and from Sweden as a function of change in total transport volume

The changes in modal shares (in percent) in both tonne-kilometres and in vehicle-kilometres for transports in, to and from Sweden as a function of the change in total freight volumes are shown in Figure 4. From the figures we see that when the total transport demand increases, the modal share of sea transport in Sweden increases at the expense of mostly road and to lesser part rail.

The non-linear responses in the model can therefore transform uncertainty in the PC-matrices to uncertainty in the estimated modal shares.

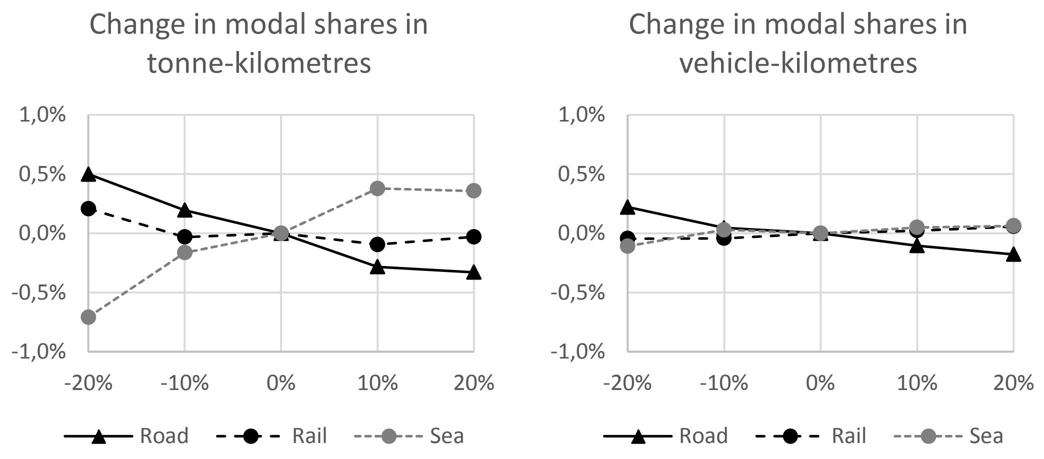

Figure 4. Change in modal shares in tonne-kilometres and vehicle-kilometres per mode inside and outside Sweden as a function of change in total transport volume

5.3 Estimation of the economies of scale

Figure 5 shows the change in total logistics cost, transport cost, order cost and holding cost (in percent) as a function of change in total transport volume. From the figure we can see that the increased transport volumes decrease the logistics costs as possibilities to exploit economies of scale and consolidation are improved and as the decrease in transport costs more than compensates the increase in inventory costs. On average, an increase in transport volumes with 10% only increases the total logistics cost with around 5%.

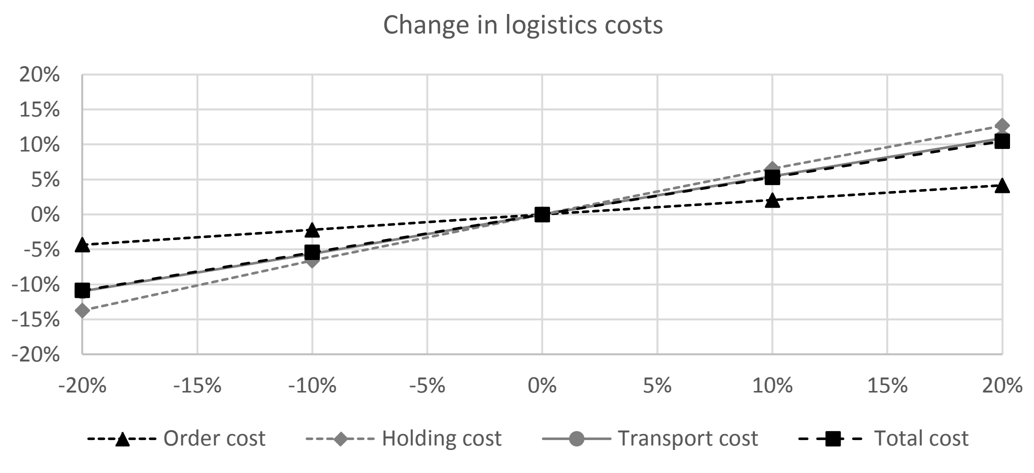

Figure 5. Changes in total logistics cost, transport cost, order cost and holding cost (in percent) as a function of change in total transport volume

To analyze the changes further we estimate the economies of scale of the model by comparing how the average logistics costs (total/transport/order/holding cost divided by total transport volume) depend on the total transport volume. Let

$$\log\left(\frac{AC_i}{AC_0}\right) = M \cdot \log\left(\frac{V_i}{V_0}\right) + k + \varepsilon_i \qquad (1)$$

where AC_0 is the average total cost per tonne in the base scenario, AC_i is the average total cost in scenario i, V_0 is freight demand volume in tonne for the base case scenario, V_i is the freight demand volume for scenario i, M is a scale parameter, k is a constant and ε_i is a normal distributed error term. Using OLS to estimate the parameter M for all commodities combined we get a scale factor M equal to -0.47. This implies that if the freight volume increases with one percent, the average cost decreases with 0.47 %. The estimated economy of scale parameters are shown in Table 4.

Table 4. Estimated scale parameters for different cost types

	Total cost	Transport cost	Order cost	Holding cost
Economy of scale parameter M	-0.47	-0.46	-0.79	-0.34

From the table we see that the scale effect is strongest for the order cost whereas the average holding and transport cost are less sensitive to the total transport volume. Separate commodity specific OLS-estimations of the scale parameters for total cost are shown in Table 5. From the analysis we see that the economies of scale in the Samgods model is relatively low for crude petroleum (that is transported by sea), iron ores, metal waste and building materials and relatively high for food and manufactured products.

Table 5. Estimated commodity specific scale parameters for total cost

Commodity	Scale M	Commodity	Scale M	Commodity	Scale M
1 Cereals	-0.52	13 Crude petroleum	-0.083	25 Transport equipment	-0.43
2 Vegetables	-0.46	14 Petroleum products	-0.36	26 Manufactures of metal	-0.62
3 Live animals	-0.31	15 Iron ore	-0.12	27 Glass, ceramic products	-0.66
4 Sugar beet	-0.39	16 Ores and waste	-0.32	28 Paper, paperboard	-0.30
5 Pulpwood	-0.25	17 Metal products	-0.31	29 Leather, clothing	-0.61
6 Wood squared	-0.39	18 Cement, lime	-0.40	31 Timber for sawmill	-0.27
7 Wood chips	-0.51	19 Earth, sand	-0.25	32 Machinery	-0.50
8 Other wood	-0.83	20 Minerals	-0.27	33 Paper manufactures	-0.60
9 Textiles	-0.65	21 Fertilizers	-0.33	34 Wrapping material	-0.65
10 Foodstuff	-0.62	22 Coal chemicals	-0.39	35 Air freight	-0.42
11 Oil seeds	-0.26	23 Chemicals	-0.37	All	-0.47
12 Mineral fuels	-0.22	24 Paper pulp	-0.21		

6. Concluding remarks

The paper analyzes the sensitivity of the Swedish national freight model system Samgods to changes to one of its main input variables, the base matrices, and use this to calculate an estimate of the economies of scale for freight transports in, to and from Sweden at an aggregate level. This type of uncertainty analysis is very uncommon in transport analysis. The results demonstrate that the deterministic logistics model within the Samgods model system is able to find new logistics solutions and shifts freight volumes from the land based modes to sea when the total transport demand increases everything else unchanged. The shift from road to rail is not that clear. Corresponding results are computed for a decrease in transport demand. The analysis hence suggests that the non-linear responses makes the model system sensitive to uncertainties in the base matrices. Errors in the estimated base matrices may therefore have a direct effect on for instance modal-split and the choice of transport chains in the model. The analysis hence highlights the importance of analyzing model uncertainty in transport models.

The results also demonstrate a tendency to shift transport volumes to larger vehicle and vessel sizes within the modes. Furthermore, the level of consolidation is calculated to increase with increased demand. This effect can be underestimated in the model since only consolidation within 34 commodities and not across these commodities is modelled and as consolidation along the route is not taken into account.

As indicated in the empirical data, there is a positive correlation in the simulation between transport demand and the average number of tonnes per vehicle or vessel. Without further empirical data, it is however difficult to assess whether the strength of this effect also corresponds to reality. One question is to what extent the effect is caused by changes in transport demand and to what extent by changed infrastructure and policy measures.

An increase in total transport volume in, to and from Sweden in tonnes by one percent will on average reduce logistics cost per tonne by about 0.5 percent. The average order cost has the strongest scale factor (-0.79) which implies that there is a potential for shippers to benefit from larger transport volumes by sending fewer larger shipments. The average inventory cost has the lowest scale factor (-0.34).

According to the large importance of the data that describe transport demand in the Samgods model system, in-depth studies for different commodities and the application of more indicators such as load factors for different vehicle types and sizes are desirable. Results from this analysis can also be used in the production of future demand matrices and transport forecasts.

Acknowledgements

The authors would like to thank Marcus Sundberg, KTH Royal Institute of Technology, Stockholm, Sweden, for useful comments of an earlier version of this paper. The authors would like to acknowledge the financial support from the Centre for Transport Studies, KTH Royal Institute of Technology, Stockholm, Sweden. We would also like to thank four anonymous referees for their useful comments on the paper.

References

Bain, R. (2009). Error and optimism bias in toll road traffic forecasts. *Transportation*, 36(5), 469-482.

Bain, R. (2011). On the reasonableness of traffic forecasts. *TEC magazine*, May 2011, 213-217.

Ben-Akiva, M. and de Jong, G. (2013). The aggregate-disaggregate-aggregate (ADA) freight model system. In Ben-Akiva, M et al. (ed.) *Freight Transport Modelling*, Emerald, United Kingdom.

Ben-Akiva. M.A. and S.R. Lerman (1985). *Discrete Choice Analysis*. The MIT Press, Cambridge, Massachusetts.

Beser Hugosson, M. (2005). Quantifying uncertainties in a national forecasting model. *Transportation Research Part A: Policy and Practice*, 39(6), 531-547.

CPB, MNP and RPB (2006). Welvaart en Leefomgeving, Centraal Planbureau. Milieu- en Natuurplanbureau en Ruimtelijk Planbureau, The Hague.

Daly, A.J., S. Hess and de Jong, G. (2012). Calculating errors for measures derived from choice modelling estimates. *Transportation Research Part B: Methodological*, 46(2), 333-341.

de Jong, G. and Ben-Akiva, M. (2007). A micro-simulation model of shipment size and transport chain choice in Norway and Sweden. *Transportation Research Part B: Methodological*, 41(9), 950-965.

de Jong, G, Daly, A.J., Pieters, M., Miller, S., Plasmeijer, R. and Hofman F. (2007). Uncertainty in traffic forecasts: literature review and new results for the Netherlands. *Transportation*, 34(4), 375-395.

de Jong, G., Ben-Akiva, M. and Baak J. (2011). Method Report - Logistics Model in the Swedish National Freight Model System (Version 2). Significance. Deliverable 6b for the Samgods group D6b, Project 10060, Swedish Road Administration, Solna.

de Jong, G., Vierth, I., Tavasszy, L. and Ben-Akiva, M. (2013). Recent developments in national and international freight transport models within Europe, *Transportation*, 40(2), 347-371.

Edwards, H., Swahn, H. and Bates, J. (2008). Swedish Base Matrices Report, Estimates for 2004, estimation methodology, data, and procedures. *Vägverket Konsult PM*, 2008-03-13, Swedish Road Administration, Solna.

Edwards, H. (2008). Update of Samgods Base Matrices 2008. *Vägverket Konsult PM*, 2008-09-25, Swedish Road Administration, Solna.

Eriksson, T., and Ritchey, T. (2002). Scenario development using computerised morphological analysis. Paper presented at the *Winchester International OR Conference*, 2002, England

Fiorello, D., G. Huismans, E. Lopez, C. Marques, T. Steenberghen, M. Wegener and G. Zografos (2006). Transport strategies under scarcity of energy supply. Final report of the project STEPs – Scenarios for the transport and energy supply and their potential effects, Buck Consultants, The Hague.

Flyvbjerg, B., Skamris Holm, M.K. and Buhl S.L. (2006). Inaccuracy in traffic forecasts. *Transport Reviews*, 26(1), 1-24.

Rasouli, S. and H. Timmermans (2012). Uncertainty in travel demand forecasting models: literature review and research agenda. *Transportation Letters*, 4(1), 55-73.

Manzo, S. (2014). Uncertainty calculation in transport models and forecasts. PhD thesis, DTU Copenhagen.

Næss, P., Nicolaisen, M.S., and Strand, A. (2012). Traffic forecasts ignoring induced demand: a shaky fundament for cost-benefit analyses. *European Journal of Transport and Infrastructure Research*, 12(3), 291-309.

Petersen, M.S., R. Enei, C.O. Hansen, E. Larrea, O. Obisco, C. Sessa, P.M. Timms and A. Ulied (2009). Report on transport scenarios with a 20 and 40 year horizon. TRANSVISIONS. Final Report for DGTREN, Copenhagen.

RAND Europe (2005). Uncertainty in traffic forecasts: literature review and new results for the Netherlands. WR-268-AVV. Report prepared for AVV Transport Research Centre, RAND Europe, Leiden.

Transport Analysis (2016). Statistics, Stockholm. Available from http://trafa.se/.

Vierth I., M. Lord and J. McDaniel (2009). Representation of the Swedish Transport and Logistics System (Logistics Model Version 2.00). *VTI notat*, 17A, VTI, Stockholm.

Westin, J. Kågeson P. (2012). Can high speed rail offset its embedded emissions? *Transportation Research Part D: Transport and Environment*, 17(1), 1-7.

Vierth, I. (2005). Transportprognoser sedan 1975. *SIKA report*, 2005:4, Stockholm.

Zhao, Y. and K.M. Kockelman (2002). The propagation of uncertainty through travel demand models: an exploratory analysis. *Annals of Regional Science*, 36(1), 145-163.