PETRA

The Travel Demand Module - Estimation and Validation

PETRA Working Paper no. 7

September 1998

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1 Introduction and Summary

1.1 Introduction

The PETRA system consists of a number of econometric models, at a disaggregate behavioural level, that endeavour to represent national travel demand in Denmark, under a number of different scenarios. The primary objective underlying the development of the system has been to provide a mechanism that allows the impact of discrete policy measures to be assessed in a robust manner. A secondary objective is that the developed model should contribute to an extension of the planning capability in national transport policy-making.

The attainment of these objectives required the development a series of disaggregate models, that endeavoured to recreate individual and household behaviour in a wide number of areas; whether to own a car, choice of mode and destination, frequency of travel, etc. These models cumulatively form the PETRA system, which can be used to identify the efficacy of different policy measures, under different scenarios.

One of the most significant models in the system is the Travel Demand Module (TDM), which endeavours to simulate the travel behaviour of individuals, at the disaggegate level. At the most general level, the TDM predicts car availability for each household in the model population. More specifically, the TDM predicts the probabilities for choosing different combinations of travel purposes and travel patterns, depending on the status of car availability.

This report provides a detailed exposition of the development of this model, which introduces a new approach to the modelling of individual behaviour, in respect of choice of mode and destination for both single and multiple trips, and the decision process of the individual in respect of aggregation.

1.2 Summary

The Travel Demand Module (TDM) is one of the more significant elements within the PETRA system. The TDM consists of a number of discrete submodels that attempt to represent individual and household behaviour in a number of areas, including licence holding, and cohort effects, changes in the extent and composition of the car fleet, and mode and destination choice.

However, the model also introduces a new approach to the modelling of mode and destination choice, for both single and cumulative journeys. The Chain Choice model tries to explain individual choice between thirteen possible chains, where a chain is defined as an aggregate sequence of tours that an individual can undertake during a day. A tour is defined as the trips, or sequence of trips, that an individual undertakes between departing from, and returning to the place of residence. The choice includes the option of staying at home.

The Chain Choice model uses the measure of accessibility, the logsum, derived from the mode and destination choice models, in addition to socio-demographic variables to explain chain choice. This model is an extension of the idea underlying the traditional frequency model, and has been inspired, in part, by the developments in activity based modelling.

The objectives of this part of the overall project have been realised, as the model system is capable of close reproduction of the observed behaviour and generally responds as expected to changes in the variables, exhibiting consistent and plausible reactions, for the constituent parts of the TDM. The mode and destination choice models appear to work well, and the distinction between tour types is significant and is strongly justified.

The Chain Choice model, in particular, has been very successful, assigning the probabilities that individuals will choose various combinations of tours. However, the model does not appear to respond to the degree expected, with respect to changes in accessibility, and the report offers some suggestions as to the potential improvements in the model in future work. One of the most significant weaknesses is perceived to be the rather limited variation offered through the use of one years cross-sectional data. This limitation has been particularly pronounced in the relative lack of response to changes in the price of fuel in the model.

The general model structure is provided in Chapter 2, while the Mode and Destination Choice models are detailed in Chapter 3. The Chain Choice Model is detailed in Chapter 4, while a description of the Car Availability model is provided in Chapter 5. The references in the text have been annotated, and a comprehensive bibliography has been provided in section 6.1.

2 General Model Structure

Car availability

The travel demand module, TDM, consists of a number of discrete models at three levels: The top level model concerns the decision of the household in respect of car availability, and a detailed exposition is provided in Chapter 5. Car availability is assumed to depend on the socio-demographic characteristics of the household, and on the accessibility, both with or without car, to different types of destinations. This form of accessibility measure has been derived from the middle level model, which is concerned with the choice of travel chain for a particular individual in the household.

Chain choice model

In context of PETRA, a chain is defined as the aggregate sequence of tours that an individual undertakes during a day, and a tour is defined as aggregate sequence of trips, or trip, undertaken by an individual between a departure from, and returning to, their place of residence.

In the chain choice model, a chain can consist of up to two tours and there can be two destinations on some tours. The chain choice model, which is described in more detail in Chapter 4, models the individual choice between thirteen possible chains, one of which represents the option of staying at home.

Mode and destination choice

The chain choice model also uses the measure of accessibility, in addition to socio-demographic variables, to explain chain choice. The measure of accessibility is derived from the mode and destination choice model, which is at the lowest level of the TDM hierarchy.

The mode and destination choice model is divided into eleven sub-models for mode and destination for various types of tour. The models and tours are detailed in Chapter 3.

2.1 The Logit Model

The logit framework is employed for all the models within the TDM, and this section provides a brief review of the logit model. Interested parties can find a more detailed exposition of the use of logit models in transportation modelling in [3].

The logit model predicts probabilities for choice between mutually exclusive alternatives based on stochastic utility maximisation.

Utility functions

A utility function, or indirect utility function, since it identifies the utility achieved if that alternative is chosen, is specified for each alternative. The utility functions are usually specified as linear combinations of both parameters to be estimated, and variables.

$U_i = \beta_i X$

The variables can describe both the alternative, and the individual making the choice.

However, the utility functions do not describe the individuals and the choice alternatives perfectly. There is an error, which is interpreted as the difference between the specified utility and the true utility. Thus, we can write

$U_i = \beta_i X + \varepsilon_i$,

where ε_i is the error associated with alternative i.

Choice probabilities

The tenet of utility maximisation asserts that an individual selects the particular alternative that provides him with the highest utility. The utility is stochastic from the point of view of the model and, hence, only the probability for a particular choice can be computed. The probabilities depend on β_i, the parameter vectors.

$P(i) = P(U_i = \max_j U_j) = P(\beta_i X + \varepsilon_i = \max_j(\beta_j X + \varepsilon_j))$

An explicit functional form for the choice probabilities can be ascertained, through the use of certain assumptions for the statistical distribution of the ε_i. This allows the calculation of the probabilities for all values of β_i.

Estimation

The problem of estimation is to determine β_i. This is undertaken through the use of a maximum likelihood procedure, such that the resulting calculated probabilities predict the observed actual choices as closely as possible.

A number of measures are employed to assess the estimation results; one of which is the $Rho^2(0)$ value, which is the relative improvement in the ability to explain the observed choices that results from using the estimated β, rather than just β=0. Having β=0 is equivalent to having no model at all.

If $Rho^2(0) = 0$ then the estimated model does not explain anything. If on the other hand $Rho^2(0) = 1$ then the model explains the data perfectly. However, the attainment of such a perfect fit with the data, is unrealistic in principle, and values above 0.5 are rare. There is, however, no absolute scale with which to compare $Rho^2(0)$ values, and the judgement of the results of a particular model is inherently subjective.

A similar measure is $Rho^2(C)$, which is computed just like $Rho^2(0)$. The difference is that $Rho^2(C)$ compares the estimated model to a model that assigns constant choice probabilities to all observations; the variables are not used make predictions. Thus, the $Rho^2(C)$ measures how much the variables, other than constants, contribute to the explanation of the model.

A model with constants only is better than no model, so the improvement of the estimated model relative to a model with only constants, is smaller than the improvement relative to no model. Thus, one would expect that $Rho^2(C)$ will be smaller than $Rho^2(0)$. This apart, all comments to $Rho^2(0)$ apply equally to $Rho^2(C)$.

A further measure is the t-value, which measures the contribution of the individual parameters in the β_i vectors. Numerically high t-values imply that the corresponding parameter is important for explaining the data. If a t-value is lower than 2, then the parameter can be dropped from the model without significantly reducing the fit.

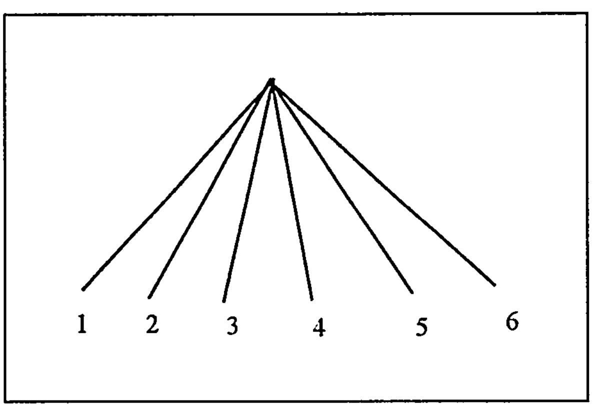
This does not imply that parameters with low t-values should automatically be dropped, and economic theory advises the retention of all variables, as a low t-value merely implies that the hypothesis that it equals zero cannot be rejected statistically.

2.1.1 Nested models

In the simple model, all error terms are assumed to be independent and identically distributed. However, this assumption is unrealistic in some situations. An example might be a combined mode and destination choice model, where a likely hypothesis is there are error terms for each mode that are common for the destination alternatives using the mode. This form of correlation is captured with a nest structure in the nested logit model.

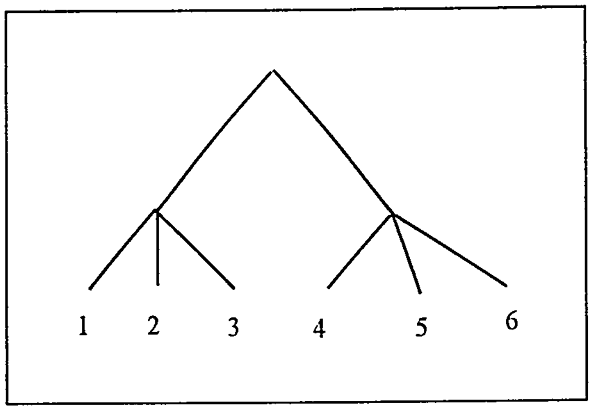
A simple logit model is often illustrated with a tree as in Figure 2-1.

Figure 2-1. Simple logit model



A nested model could have the more complicated structure shown in Figure 2-2. The upper part of the tree could correspond to two modes with three destination alternatives for each mode.

Figure 2-2. Nested logit model



The structure indicates the error term for each intermediary node. The correlation thus introduced has implications for how the model will react to changes in utility.

If the utility for alternative 1 is decreased, then the probability for alternative 1 will also decrease, and the probabilities for all other alternatives will increase. This is true both for the simple and the nested model. The difference is that the probabilities for alternatives 2 and 3 will increase more, and the other probabilities increase less in the nested model than in the simple model.

The use of the nested structure brings structural parameters that measure the size of the common error terms. These parameters must be between 0 and 1 for the model to behave in a consistent manner with the theory.

2.1.2 Accessibility measure

Logsums

The logit model can be derived from economic utility theory, and the link provides an interpretation of a variable that can be computed from the model; this variable is known as the logsum. This can be interpreted as the utility associated with all the choices in the model assumed to sum to one.

A high logsum for a particular individual implies that the sum of choices is attractive, while a low value implies the reverse.

When the model concerns travel choices, as it does here, the logsum can also be interpreted as the accessibility associated with the model alternatives. These accessibility measures are used extensively in the TDM.

One example might be in a model of destination choice, the utility for a particular destination is computed such that the utility increases if the destination is attractive, and decreases if the destination is expensive to reach. The logsum, of such a model, is a kind of a weighted average utility and would represent the utility of going somewhere in general, rather than to a specific destination. The logsum expresses accessibility such that a higher accessibility results, if many destinations can be reached at low cost, and/or if attractive destinations can be reached at low cost.

3 Mode and Destination Choice

Mode and destination choice sub-models have been estimated for 11 distinct tour types. This chapter describes the data used for estimation in section 3.1, while section 3.2 provides a detailed exposition of the model structure. The results of the estimation are provided in section 3.3, and are discussed in section 3.4.

3.1 Estimation Data

Weights

Weights are applied to the data in all the estimations, and are intended to correct for sampling biases that have occurred in the data during collection. The calculation of the weights is detailed in [6].

3.1.1 Travel purposes

Four destinations

Four types of destinations are used in the model: One is entitled home, the other three are destinations, where some primary activity is engaged in which is the rationale for travelling. For convenience, they are coded with the numbering provided in the following table. A detailed definition is provided in [1].

1.	Home	The residence of the Interview Person (IP)
2.	Work	Work, business, education
3.	Errand	Errands of all kinds, including shopping, collecting and bringing children
4.	Leisure	Visiting family or friends, amusement, weekend cottage, excursion, sport, meeting and walk

3.1.2 Simple and triangular tours

The definition of tour types, together with a detailed description of the transformation of observations in the TU data, to conform with the definition is given in [1]. A brief review of the definitions is provided in the following sections.

Home based tours

All tours are assumed to be home-based, i.e. that they start and finish at home. A tour can be either simple or triangular, where a simple tour could be, e.g., 121 (i.e. home - work - home) and a triangular tour could be 1231 (i.e. home - work - errand - home).

Main and minor tours

A distinction is drawn between main and minor tours in the following way: Tours including a work destination are always main tours, whilst work cannot occur on minor tours.

A tour like 131 is considered to be a main tour, if, and only if, it is the only tour in the travel diary. If it follows another tour, e.g., to work, it is treated as a minor tour in a different sub-model.

Definitions

The tour types are presented below, together with the naming convention adopted for the sub-models. Tours are divided into three groups, with the first group comprising simple main tours, or tours with the following purposes

Name	Sequence
12	Home - work - home
12x	Home - work - home, followed by a minor tour
13	Home - errand - home
14	Home - leisure - home

The second group consists of triangular main tours.

Name	Sequence
123	Home - work - errand - home
123x	Home - work - errand - home, followed by a minor tour
124x	Home - work - leisure - home, followed by a minor tour
134	Home - errand - leisure - home

Finally, the third group consists of simple minor tours.

Name	Sequence
214	Home - leisure - home, following a work tour
314	Home - leisure - home, following an errand tour
x13	Home - errand - home, following any main tour

3.1.3 Modes

The model operates with distinct six modes. The modes have been defined to represent an aggregation of the more detailed definition of modes employed in the TU. They are presented in the following table.

Table 3-1. Definition of modes

Model mode	TU modes
Walk	Walk
Bicycle	Bicycle, moped
Car	MC, car, taxi, truck driver
Car passenger	Car passenger
Bus	Bus, S-train
Train	Train

Observed mode choice

The observed distribution of tours by mode, for the different tour types is provided below, whilst a number of observations are made.

- The walk mode is used primarily for simple tours, on errand or leisure purposes.
- The bicycle mode is predominantly used for tours involving the journey to work.
- The car mode has the largest share of tours of all types. Its share is highest for triangular tours and for errand trips after returning from work.
- The car passenger mode is most common for leisure tours.
- Bus is less used for secondary tours, most for simple work tours and triangular tours with work and leisure.
- Train is the smallest mode, and is little used for secondary tours.

Table 3-2. Number of tours by mode and tour type

Tour type	Walk	Bicycle	Car	CP	Bus	Train	Total
12	7.1%	19.5%	50.3%	8.0%	12.1%	2.9%	2,303
12x	9.2%	26.7%	46.2%	8.2%	7.8%	1.8%	1,878
13	22.0%	9.2%	51.0%	10.7%	6.4%	0.7%	2,084
14	19.2%	10.0%	41.8%	22.1%	5.9%	1.0%	2,603
214	17.3%	17.0%	46.7%	13.5%	4.9%	0.5%	1,109
314	19.9%	11.1%	50.3%	16.1%	2.3%	0.3%	342
cx13	21.6%	11.6%	58.9%	6.4%	1.3%	0.2%	1,007
123	3.9%	16.3%	62.8%	6.9%	9.0%	1.2%	669
23x	6.6%	19.4%	61.4%	6.0%	5.2%	1.4%	484
24x	3.3%	21.4%	48.7%	10.8%	13.3%	2.5%	398
134	8.7%	8.0%	56.1%	20.5%	5.8%	1.0%	415
Total	14.1%	15.6%	49.7%	12.1%	7.1%	1.4%	13,292

The total sum of 13,292 tours does not tally with the number of respondents in the sample (13,545) for two reasons: Firstly, those who did not undertake a trip (approximately 3,000 persons) are not included here, and secondly, persons who undertook both a main and a minor tour are counted twice.

The differences in modal shares, across tour types, are significant and have plausible interpretations. This strongly supports the employed approach, where mode and destination choice is modelled separately for each tour type.

Observed length

Table 3-3 provides the average length of tour, by observed mode and tour type. We note that walk and bicycle tours have the shortest length, whilst car and bus tours are about the same length, with train tours being a little longer.

In general, minor tours tend to be shorter and triangular tours tend to be longer. Tours with errands tend to be shorter, and tours involving leisure tend to be longer.

Table 3-3. Average length by mode and tour type, km

Tour type	Walk	Bicycle	Car	Car Passenger	Bus	Train	Bus to train
12	3.6	7.9	41.6	32.7	38.5	75.6	5.0
12x	3.7	7.1	33.1	25.1	32.9	78.1	4.1
13	3.3	5.0	23.1	27.0	23.4	68.0	3.1
14	3.7	8.1	43.7	47.1	47.2	101.2	5.1
214	3.6	7.6	23.9	27.7	30.2	78.4	2.3
314	3.5	5.2	20.6	23.3	22.8	42.2	1.7
cx13	3.1	4.5	15.5	26.3	24.9	45.2	5.9
123	5.6	8.7	38.2	30.4	40.5	51.2	16.1
23x	4.9	8.8	31.1	21.2	35.0	78.8	11.1
24x	6.6	10.8	53.1	44.8	52.7	80.1	12.5
134	5.9	7.6	44.5	58.5	49.7	180.3	10.4

Expected distance

The observed distribution of observations on modes, and the observed average tour length per mode, allows the calculation of the expected distance per mode by multiplying the two tables. The results are illustrated in Table 3-4, and can be interpreted in the following way; the average tour of type 12 consists of 0.3 km by walk, 1.6 km by bicycle, etc.

Table 3-4. Expected distance per mode

Tour type	Walk	Bicycle	Car	CP	Bus	Train	Total
12	0.3	1.6	20.9	2.6	4.8	2.2	32.3
12x	0.3	1.9	15.3	2.1	2.7	1.4	23.7
13	0.7	0.5	11.8	2.9	1.5	0.5	17.9
14	0.7	0.8	18.3	10.4	2.8	1.0	34.1
214	0.6	1.3	11.1	3.8	1.5	0.4	18.7
314	0.7	0.6	10.3	3.7	0.5	0.1	16.0
cx13	0.7	0.5	9.1	1.7	0.3	0.1	12.4
123	0.2	1.4	24.0	2.1	3.8	0.6	32.2
23x	0.3	1.7	19.1	1.3	2.0	1.1	25.5
24x	0.2	2.3	25.9	4.8	7.3	2.0	42.6
134	0.5	0.6	25.0	12.0	3.0	1.7	42.8

Minor tours tend to be short, in line with a priori expectations. Of the simple main tours, errand tours, 13, are the shortest, leisure tours are the longest. Work tours followed by another tour, 12x, are shorter than single work tours, 12. This pattern is repeated for triangular tours with work and errands, 123 and 23x. Leisure tours tend to be longer, we note for example that both 214 and 314 are longer than cx13.

Generally, the differences in tour lengths are plausible.

3.1.4 Cost data

Variable cost

The model uses a variable cost per kilometre for the car mode, which is assumed to include the cost of petrol only, excluding other variable costs like lubricants, tyres, repairs and depreciation. This is unsatisfactory from an accounting perspective, but the underlying assumption is that people generally only consider the direct fuel costs when making everyday travel choices. The other costs are assumed to enter into the car ownership decision.

This view is supported by interviews with car users ([8]), where only 14% of respondents could provide an indication of the variable costs for a specific trip, other than fuel costs. Of the 14%, 5% stated insurance premiums and annual taxes which do not qualify as variable costs in the usual sense.

In the case of car passengers, a unit cost per kilometre of half the fuel cost is employed. This is an ad hoc approximation, but we feel it is justified, as we believe that variable costs do have an influence on CP destination choice and further that variable costs influence the choice of the mode. When the CP mode is chosen there are (at least) two persons in the car, and thus only half the costs accrue to each person.

Calculation of PT fares

The calculation of fares for public transport (PT) is described in [1].

PT fares in Denmark are based on the number of tariff zones through which the bus or train passes, from the starting point to the destination. The number of tariff zones for each alternative trip, is calculated by transforming bus and train distances to a number of tariff zones, according to the average tariff zone size in the different counties in Denmark.

The fare for each destination alternative is calculated, according to the tariff systems of the counties involved.

Tax deductions

Tours to work do not carry the full cost, since a tax discount is given according to the distance from home to work. This discount is subtracted from the costs used in the models.

The value of the discount is 0 DKK per kilometre for the first 24 kilometres per day, 0.56 DKK per kilometre for the next 75 kilometres and 0.28 per kilometre for following kilometres (beyond 100 kilometre per day). This is predicated upon a tax rate of 0.46 percent.

3.2 Model Structure

3.2.1 Destination sampling

The inclusion of all the TU zones as destination alternatives, is beyond the capability of existing computation capacity. Therefore, each model contains only a limited number of destination alternatives, selected from all the TU zones using random stratified sampling. The procedure has been detailed in [1]. After sampling, the selected destination has been exchanged for a sampled destination in the corresponding stratum.

For the simple models, 9 destinations have been sampled. In the case of the triangular models, 9 primary destinations have been sampled and for each of these 4 secondary destinations have been sampled.

3.2.2 Correction for destination sampling

The utilisation of maximum likelihood estimation of a statistical model entails specifying the likelihood of obtaining the observations available in a sample, as a function of a parameter vector. The maximum likelihood estimator being that vector that maximises the likelihood of obtaining the actual sample.

The likelihood for an observation consists of two parts: The likelihood that the observation is as selected, and the likelihood that the observation is included in the sample. The latter part is generally ignored as it cancels out in most situations. However, this is not the case here.

The sample of destinations is considered to be part of the observation. The possible destinations occur in the sample with varying probabilities depending on the location of the residence of the IP, and on the stratum corresponding to the destination. Since the probabilities are not equal they do not cancel out in the likelihood function. and it is necessary to include terms that reflect that variation in probability.

The calculation of factors to correct the likelihood for destination sampling is described in [1], and a general introduction to the subject can be found in [3].

3.2.3 Nest Structure

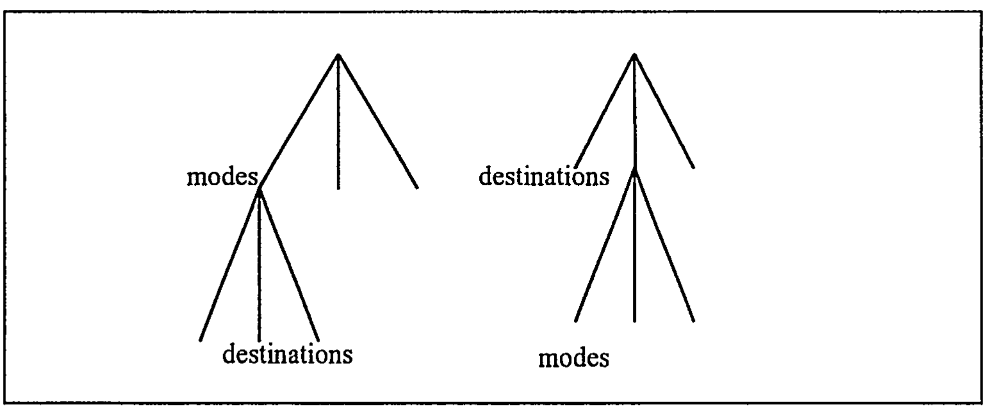
Two different nest structures have been tested with either destination or mode choice on top (Figure 3-1).The structure with mode choice on top, was found to have consistent values for the structural parameters in the majority of cases, in contrast to the former structure.

Mode choice on top

In the final models, mode choice is on top in all cases, except three, where a nest structure could not be reliably estimated.

Only one structural parameter, common to all modes, is estimated. This is because the utility functions contain a number of generic variables, i.e., for cost, time and attraction measures. Had there been more structural parameters, then a change, e.g., in attraction for some destination would imply a shift in mode choice which is unreasonable. The issue is discussed in [9].

Figure 3-1. Nest structures



3.2.4 Data transformations

Car distance and car time is calculated using a GIS based system. Road maps of Denmark have been translated to centroids. The distance between two locations is measured as the sum of the direct line distance between the centroids, placed on the roads[1] between these two locations. This method of calculating the straight-line distance between the centroids, inevitably results in some under-

[1] The centroids are placed at every cross road.

estimation of the true distance between the two points, the extent of which has been estimated by DMU[2], to be approximately 4 percent on average.

The distance between locations using the other modes: walk, bicycle and car passenger, is assumed to be equal to the car distance.

The distance by bus is assumed to be longer than car distance, as the bus does not generally take the shortest route. A minor study was used to provide the basis for a regression to identify the following relationship between bus distance and car distance:

$$bus\ distance = 3.6+1.13*carkm.$$

It seems reasonable to assume some positive constant term, since the bus neither stops right at your front door, nor stops exactly where you want to go[3].

Train distance is calculated as the car distance between the two train stations that are located closest to the starting point and the destination point respectively.

Income questions traditionally yield low response rates, and the data in the sample are based on telephone interviews. In the TU data, approximately one third of respondents could not, or would not, answer the income questions. The response rate to questions about family income, is understandably the lowest, reflecting the degree of uncertainty about total family income among the constituent members of the family.

Since partial drop out on income questions is not equally distributed over socio-economic and demographic groups, the problem cannot be solved through the simple exclusion of those observations with missing income information. This would lead to a more skewed sample.

A refusal to answer income questions is handled by assuming that the individual has the same income as the average in their respective socio-economic group. This is still somewhat problematic, since it is known that often people who decline to answer income questions diverge from those able, or willing, to reveal their income. However, it would be more erroneous to assume that their income is the same as the total average. The deletion of these individuals from the sample would also be unacceptable, because of the loss of information and because of the risk of introducing bias in the remaining sample.

The issue is handled by assuming that the individual with missing income has the same income as the average in their respective socio-economic group.

Both income before and after tax is reported in the interview. In the present data material income information is categorised in DKK 25.000 intervals:

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[2] E-mail from DMU of 26th of march 1997.

[3] Because of the definition of main mode for the whole trip all transport including walk or bicycle to the bus stop is calculated as bus km.

1. DKK 0 - 24,999 per year
2. DKK 25 - 49,999 per year
3. DKK 50 - 74.999 per year

and so forth

For estimation purposes, the income is calculated as:

*income = income group * 25.000 - 12,500*

3.2.5 Utility functions

An utility function is specified for each mode and destination alternative. They combine three elements, generalised cost, attraction and individual specific variables.

The generalised costs encompass the monetary and time costs associated with reaching a destination by a particular mode. The higher the cost of reaching a destination by a particular mode, the lower the utility.

The costs are balanced by attraction variables associated with the destinations, that are independent of the mode. The attraction variables employed, measure the size of the destination zones in terms of population and employment in different categories. A large zone is a more likely choice than a small zone, all else being equal.

Attraction and generalised costs can compensate for each other, such that a large zone can be unattractive even though the costs of reaching it are low, or a small zone can be attractive even if the costs of reaching it are high.

The cost and attraction variables generally do not reflect anything about the individual making the choice. The exception are some attraction measures that are only used for some socio-demographic groups.

The utility functions also contain a number of individual specific variables, associated with the choice of mode. These can be dummies showing how females are more likely to travel as car passengers, or variables reflecting the licence holding and car availability status of the household.

The formulation of utility functions is illustrated with the ch12 sub-model as example.

Table 3-5. Combination of variables and parameters by mode in ch12

	Walk	Bicycle	Car	CP	Bus	Train
Mode specific constant	p111	p121		p131	p141	p151
Tax discount		p101	p101	p101	p101	p101
Cost			p101	p101	p101	p101
Time	p112	p112	p112	p132	p112	p112
Female dummy				p231		
Cars per licence			p126			
No car in household			p128	p129		
Single woman	p313	p313				
HT area					p146	
LoS bus (destination)					p142	
Young woman dummy					p441	p441
Old woman dummy					p341	p341
Single					p145	p145
Log of employment	p170	p170	p170	p170	p170	p170
Walk distance to station						p156
LoS train (destination)						p154
Logit(education) only Female Student	p176	p176	p176	p176	p176	p176
Logit(transport) only workers and "lower white collar"	p178	p178	p178	p178	p178	p178

Each mode has a mode specific constant, excepting the car mode which is used as the base. A generic variable, Cost and tax discount, is used as the same parameter for all the modes[4]. This also holds for time, with the exception of car passenger time.

The car passenger mode has a sex specific dummy, reflecting that women are more likely to travel as car passengers.

Car availability

The number of cars per licence in the household is used to measure the availability of the car mode and a positive parameter is expected. If there are no cars in the household then the likelihood of choosing car or car passenger decreases.

Attraction parameters

The log of employment is a measure of the size of the destination zone. In the case of work trips, parameters should be between 0 and 1. The size measure is then simply a count of the available alternatives at each destination, and the parameter is a sort of logsum parameter.

Furthermore, the logit (log(empl.education/(total empl. - empl.education)) of the number of employees in special branches is included for specific groups.

[4] However, since the tax discount is always zero for walk mode (distance < 25 kilometre) the tax discount parameter is not included in the walk mode.

Group 2 sub-models with two destinations are different; Firstly, group 2 models include a detour, the cost of which is calculated as the marginal extra cost related to the detour. When train is the main mode of the trip it is assumed that the detour is carried out by bus, if the distance is longer than one kilometre and walking, if the distance is shorter than one kilometre.

Secondly, extra attraction variables and LoS variables are included for the destination of the detour.

The bus and train modes are treated as one public transport mode in those submodels where the number of observations that choose train is limited.

A remark on formulation

Care has been taken to formulate the utility functions to ensure that the logsums express accessibility as well as possible. The issue can be illustrated by a simple example: Let us say we have a model with two alternatives, If some (socioeconomic) group has a higher propensity to choose alternative 1, then this may be captured by a dummy that can be in either utility function. If the dummy is placed in alternative 2, then it becomes negative and the logsum will be smaller for observations from the group. The reverse is true, if placed in alternative 1.

Thus, the placement of the dummy is important. The effect must be interpreted as one that either detracts from the utility of one alternative, or adds to the utility of the other.

It is necessary to be aware of the effects, and ensure that all variables have a reasonable interpretation, when the logsum is used as a variable in further modelling as it is in the TDM.

3.3 Estimation results

3.3.1 General results

Table 3-6 shows summary statistics for the estimations of the 11 sub-models.

Table 3-6. Summary statistics

Model	Observations	Likelihood at zero parameters	Final likelihood	$Rho^2(0)$
12	2303	-8372	-5011	0.40
12x	1878	-6948	-3977	0.43
13	2084	-7985	-4330	0.46
14	2603	-10041	-7109	0.29
123	668	-3271	-1834	0.44
23x	484	-2350	-1395	0.41
24x	398	-2159	-1241	0.43
134	415	-2261	-1543	0.32
214	1109	-4129	-2675	0.35
314	342	-1266	-767	0.39
x13	1007	-3655	-1750	0.52

If one considers the $Rho^2(0)$ values, then the fit of the sub-models is generally good. It should be noted that the models with zero parameters still contain the factors that correct for the sampling procedure. Thus, the $Rho^2(0)$ measures are relative to the case where correction for the sampling procedure has been made.

3.3.2 Cost variables

Table 3-7 illustrates the estimated parameter values for the cost variables. The time parameter covers time in all modes, with the exception of the car passenger mode, for which a separate time parameter is estimated.

The signs of all the parameters is in line with a priori expectations. Parameters for cost and, in particular, time and car passenger time are very significant. GaaBus and GaaSta, indicators of the distance from home to the nearest bus stop and railway station respectively, are barely significant and are excluded in those cases where they enter with the wrong sign.

Table 3-7. Cost variables, t-values in parentheses

Model	Cost	Time	CP Time	GaaBus	GaaSta
Parameter	p101	p112	p132	p149	p156
Alternative	All	Not CP	CP	Bus	Train
12	-0.0207 (-3.3)	-0.0379 (-45.3)	-0.0655 (-16.8)		-0.4141 (-4.2)
12x	-0.0305 (-2.9)	-0.0478 (-40.3)	-0.0786 (-13.3)	-0.6324 (-2.0)	-0.8540 (-3.1)
13	-0.0251 (-4.6)	-0.0612 (-28.0)	-0.0582 (-13.1)	-1.1915 (-2.5)	-1.4235 (-3.1)
14	-0.0120 (-5.1)	-0.0328 (-32.7)	-0.0365 (-25.4)	-0.2377 (-1.7)	-0.2172 (-1.6)
214	-0.0398 (-6.3)	-0.0462 (-20.9)	-0.0460 (-9.4)	-1.4449 (-1.3)	
314	-0.0606 (-4.4)	-0.0536 (-11.2)	-0.0609 (-6.8)		
cx13	-0.0750 (-7.0)	-0.0761 (-20.6)	-0.0577 (-7.2)		
123	-0.1210 (-10.0)	-0.0645 (-24.8)	-0.1084 (-9.4)		
23x	-0.1716 (-10.0)	-0.0778 (-25.4)	-0.1727 (-8.6)		
24x	-0.0328 (-4.1)	-0.0428 (-18.0)	-0.0683 (-10.2)		
134	-0.0284 (-3.6)	-0.0501 (-14.7)	-0.0465 (-9.9)	-3.7036 (-1.6)	

The parameter estimate of the time variable compares with the figures in the mode distance choice models in TØI [14]. In TØI, there are estimated time parameter estimates of -0.045 to -0.075, dependent on the purpose of the trip. Table 3-7 shows time parameter estimates from -0.037 to -0.076 dependent on the tour type.

It is useful to compare the values of time (VoT) inferred from these estimates. The implied value of time is the value at which time and monetary cost are traded off in the utility functions. The values of time implied by the parameters are shown in Table 3-8.

Table 3-8. Implied values of time, DKK per hour

Model	Time	CP Time
12	110	190
12x	94	155
13	146	139
14	164	182
214	70	69
314	53	60
cx13	61	46
123	32	54
23x	27	60
24x	78	125
134	106	98

Generally, the value of time (VoT) is in a plausible range for all sub-models, and the VoT is generally higher for car passengers than for the other modes.

The highest VoTs occur for simple work tours, 12 and 12x, and for the simple leisure tour, 14. The lowest VoTs occur for the triangular tours involving both work and errands, 123 and 23x.

There are large differences in the VoT for different tour types. This could be evidence of a sample selection bias, whereby IPs with a low VoT are more likely, e.g., to do the errands on the work tour than IPs with a high VoT. This issue is investigated in section 3.4.2.

It should be noted that the specification of costs has large implications for the VoTs. The main part of the costs are constituted by car costs. Specifying higher costs per kilometre would result in a lower cost parameter end hence higher calculated VoTs. Further, cost is a generic variable with the same parameter being applied to costs in all modes. This allows the estimation to get around the problem of correlation between distance and time in the car network. Thus, it is the variations in mode choice that determines the relative size of the cost and time parameters and hence the VoTs.

3.3.3 Level of service variables

A few indicators for the level of service (LoS) with public transport have been available. Corresponding parameters are only included in the cases where they come out with the intuitively correct sign. Table 3-9 illustrates this only applies in a few cases, and generally those parameters allowed to enter are not significant. From a forecasting perspective, this is unfortunate since the models cannot be expected to fully predict the effect of service improvements for public transport.

The variables corresponding to the parameters in the table, are in terms of the number of daily departures. P refers to primary destinations, S to secondary destinations on triangular tours. Bus and Trn refer to bus and train modes, Ds and Bo refer to the level of service at the destination and residence zones. Thus, the LoS variable with the greatest explanatory power is the number of departures by bus from the (primary) destination zone.

Table 3-9. Level of service variables, t-values in parentheses

Model	PBusLsDs	SbusLsDs	PTrnLsDs
Parameter	p142	p143	p154
12	0.0005 (4.1)		0.0006 (5.0)
12x	0.0005 (2.2)		
13	0.0017 (6.2)		
14	0.0009 (5.4)		
214	0.0004 (0.9)		
314	0.0003 (0.4)		
cx13	0.0011 (3.2)		
123		0.0015 (4.7)	
23x		0.0010 (2.2)	
24x		0.0005 (2.0)	
134		0.0001 (4.7)	

Level of service with bus at primary destinations works quite well for the simple tours (PBusLsDs). Level of service with bus at secondary destinations works as well for triangular tours (SBusLsDs). Level of service for train at primary destinations enters only for chain 12.

3.3.4 Attraction variables

A number of attraction variables are assigned to each destination zone. They are listed in the following four tables.

Choice of attraction variables

A number of possible attraction variables have been available. They were screened using regression techniques to identify candidate variables for the models.

The best model would employ a proper size measure as this has a theoretical interpretation in terms of elementary alternatives being available within each destination zone. However, to make estimation of the complicated models feasible it has been chosen to adopt an approximation to a size measure.

A main attraction variable enters in each model, either total employment or population in the zone transformed to logarithms. All other attraction variables are employment in different sectors. They are transformed to be the logit of the share of total employment. In this way they represent the deviation from the average zone in the composition of employment.

The first two columns in Table 3-10 illustrate the main attraction variables. For tours where work is the primary purpose, the log of employment (PBskStAr) in the destination zone is used. The log of population (Befolkn) is used for the other tours, except 13.

Table 3-10. Attraction variables, t-values in parentheses

Model	PBskStAr	Befolkn	GymStudF	OFLArbL
Parameter	p170	p190	p176	p178
12	0.8215 (39.1)		0.4949 (5.7)	0.2165 (5.7)
12x	0.8405 (31.9)			
13				
14		0.1818 (6.0)		
214		0.2408 (3.9)		
314		0.2984 (3.1)		
cx13				
123	0.8587 (15.0)		0.6196 (2.3)	
23x	0.7773 (13.2)		1.6108 (3.2)	0.1737 (1.8)
24x	0.9947 (15.4)		0.3841 (2.4)	
134				

Employment works well for work tours with very high significance levels. Population works less well for non-work tours. GymStud below measures employment in higher education and is significant for work tours that are followed by another tour, 12x. GymStudF above is the same variable with a dummy for a female IP and enters 12, 123, 23x and 24x.

OFLArbL is employment in the transportation sector with a dummy for an IP who are employed as unskilled workers. The corresponding parameter is most significant in 12, and is thought to be associated with the large number of unskilled workers employed in the transportation sector.

Table 3-11. Attraction variables, t-values in parentheses

Model	Handel1	H1s346F	H1s356M	Handel3	Transp
Parameter	p274	p252	p251	p276	p278
12					
12x			0.9607 (3.0)	0.1448 (3.2)	
13	0.3056 (5.0)			0.2903 (4.7)	
14					0.1753 (6.6)
214					0.1932 (4.0)
314					0.2211 (3.0)
cx13				0.3224 (4.0)	
123	0.0452 (0.4)	0.3815 (1.6)		0.2863 (2.8)	
23x	0.2686 (3.0)				
24x					0.2317 (3.1)
134				0.6713(16.6)	0.1217 (1.8)

Retail

Handel1, H1s346F and H1s356M is employment in other retail and service, for example car sale and repair, sale of clothes, furniture, etc. H1s346F and H1s356M are Handel1 multiplied with dummies for special segments of women and men respectively. Handel3 is employment in retail of food, pharmacies and similar. Together, Handel1 and Handel3 enter all tours including errands. Handel3 also enters in 12x, simple tours to work followed by a minor tour. Handel3 is generally the most significant of the two measures.

Transport

Transp is employment in the transportation sector, i.e. transport, post and telecommunication. The measure enters in all tours involving leisure activities.

Table 3-12. Attraction variables; t-values in parentheses

Model	Folkesk	Gymnasie	GymnStud	Uddann.
Parameter	p281	p283	p217	p284
12				
12x			0.3803 (6.1)	
13	0.0407 (0.7)			
14				0.0272 (1.2)
214	0.1676 (2.8)			0.0396 (1.1)
314				
cx13	0.1381 (1.5)			
123	0.1268 (2.0)			0.2623 (5.2)
23x	0.1273 (1.8)			
24x		0.1466 (2.8)		0.0654 (1.2)
134		0.1201 (2.4)		

Education

Folkesk, Gymnasie and Uddan is employment in education sector, i.e. teachers in primary schools, high schools and tertiary educational institutions.. The measure enters leisure activities. Not all of the variables are significant, in the strict interpretation, however, they have been retained in the model, if their sign is in line with a priori expectations. Since many leisure activities take place at, or close to, schools, it is expected that some people will travel to destinations with schools for leisure purposes.

Hospital

Hospital is employment in the hospital sector. It was expected that some of the leisure (visits) trips would involve visits to hospitals to visit friends and family. The measure only enters in 214 (work, home, visit). The effect cab is insignificant.

Restaurants

HotelRes is employment in hotels and restaurants. The measure enters significantly in leisure activities, i.e. people travelling for leisure purposes often choose destinations with many hotels and restaurants. This is in line with a priori expectations.

Table 3-13. Attraction variables, t-values in parentheses

Model	Hospital	HotelRes	PengeFin	Ofs78	OffAdm	OfadmUd
Parameter	p282	p277	p279	p253	p280	p177
12						
12x		0.1782 (3.7)				
13			0.1639 (3.5)			
14		0.1963 (6.7)				
214	0.0387 (1.2)					
314						
cx13		0.1237 (1.8)				
123			0.3494 (4.7)	0.3799 (3.7)		
23x					0.2680 (3.5)	1.4603 (3.1)
24x		0.3135 (3.4)				
134		0.3465 (4.3)				

Financial

PengeFin is employment in financial branches. The measure enters in errands, since it is expected that a significant part of errands involve trips to the bank. This effect is strongly significant.

Public adminitrattion

The last three terms are employment in public administration, specifically in special segments: OffAdm is the employment in public administration, Ofs78 is OffAdm multiplied with a dummy for white collar workers and OfadmUd is OffAdm multiplied with a dummy for males not engaged in the labour market (students, retired or unemployed).

3.3.5 Individual specific variables

The final set of variables relates to the individuals. The first group involves the licence holding and car availability status of the household.

Car availability

The NoCarC and NoCarCP dummies are 1, if the household does not have a car available. They are placed in the car and car passenger utility functions, respectively. These parameters are expected to be negative.

NoCarCP is negative in all cases as expected. The parameter is numerically smallest for simple work tours, 12 and 12x, and for simple leisure tours, 14. It seems natural that if the household does not have a car available, then people can more easily travel as car passengers on these tour types where tours are perhaps more easily scheduled.

CarPrLic is the number of cars per licence in the household and expresses the competition for use of the household cars. The parameter comes out positive in all cases as expected.

If a partner in the household has a licence then this is expected to increase the likelihood of travelling as a car passenger. The CPpartKK is a dummy for this and enters the model with the expected sign in most cases.

Table 3-14. Licence holding variables, t-values in parentheses

Name Parameter Alternative Model	CarPrLic p126 Car	NoCarC p128 Car	NoCarCP p129 CP	CppartKK p137 CP	CPLHjmF p326 CP
12	2.8493 (10.3)	-1.1123 (-4.0)	-0.6168 (-3.1)		
12x	5.6859 (7.3)	-1.6243 (-2.7)	-0.6840 (-1.6)		
13	2.8397 (4.4)	-5.2158 (-7.2)	-3.4472 (-6.1)	1.6628 (4.5)	-0.8448 (-1.9)
14	0.9760 (4.8)	-2.1199 (-9.2)	-0.8190 (-5.8)	0.5938 (4.7)	
214	4.8047 (2.6)	-9.0019 (-3.1)	-4.4857 (-2.7)	1.6585 (1.5)	
314	2.9898 (4.6)	-0.0645 (-0.1)	-1.5104 (-3.1)	0.4834 (1.1)	
cx13	1.9693 (4.4)	-2.0932 (-5.1)	-2.0033 (-3.5)	0.3297 (0.9)	-0.5292 (-1.7)
123	9.4987 (3.9)	-7.4561 (-3.3)	-4.5880 (-2.6)	1.7629 (1.2)	
23x	6.7559 (2.8)	-6.7400 (-2.8)	-2.5782 (-1.3)	1.1698 (0.7)	
24x	5.9193 (3.3)	-2.0975 (-1.7)	-4.9934 (-3.9)		
134	6.4404 (1.8)	-7.8108 (-2.1)	-3.6046 (-1.5)	7.1867 (2.4)	

CPLHjmF is the number of cars per licence in the household, multiplied by a dummy for women. It can be clearly seen that there is a significant negative estimate on two types of tours including errands. The sign is plausible since it is more likely that the woman drives, the more cars there are per licence in the household.

Selvst is a dummy for self-employed people. The latter are less likely to choose slow modes when they do a work tour and a minor tour (12x). SelvstM is a dummy for self-employed men. Self-employed men do not choose slow modes when they do errands.

StudF is a dummy for female students. Female students are more likely to chose the bus than male students (and other no students).

Single family people (Enlig) more often use public transport in work-related tours. This is expected, since car availability is lower among people living alone compared to couples. Single family women (Enlig1F) are more likely to use slow modes when whey go to work than men and people living with a partner.

Table 3-15. Individual specific variables, t-values in parentheses

Name Parameter Alternative Model	SelvstM p114 Walk, Bi-cycle	Selvst p122 Bicycle	StudF p427 Bus	Enlig p145 Bus, Train	Enlig1F p313 Walk, Bi-cycle
12				1.4821(6.7)	0.7353(3.7)
12x		-3.658(-3.2)	1.5654(3.5)	2.5939(4.7)	
13	-2.766(-2.4)				
14					
123					
23x					
24x				2.3981(3.2)	

HT is a dummy for the area near Copenhagen (Hovedstadsområdet). This area has a common tariff structure, which makes it relatively cheap to travel long distances within the area by bus. Further, a large part of this area is covered by subways, which in this context is regarded to be the same as bus.

Table 3-16. Individual specific variables, t-values in parentheses

Name Parameter Alternative Model	HT p146 Bus	HT p116 Walk, Bicy-cle
12	1.2767(8.6)	
12x	2.3177(5.7)	
13		1.0700(3.7)
14	1.3866(8.0)	
123	6.1711(3.2)	
23x	2.0513(3.2)	

The HT variable is meant to take care of these deviations from the rest of the country, and is strongly significant in most of the models. The parameter estimate indicates that there is generally more people using the bus (and subway) in the Copenhagen area, relative to the rest of Denmark. This effect is not significant on tours where the only purpose is errand.

Table 3-17. Individual specific variables, t-values in parentheses

Name Parameter Alternative Model	BsASCGF p341 Bus, Train	BsASCYF p441 Bus, Train	BusGL p148 Bus	CPASCHM p331 Car pass.	CPASCLM p431 Car pass.
12	0.6213(2.4)	0.7736(5.3)			
13			2.1061(2.7)		
14				-1.8521(-9.0)	-1.1406(-8.8)

BsACSGF is an alternative specific constant for bus and train for women at the age of 50 or older, BsACSGF is an alternative specific constant bus and train for women younger than 50. Apparently, women are more likely to choose public transport when they go to work relative to men. This effect is most significant among younger women.

BusGL is an alternative specific constant for bus for individuals at the age of 50 or older. Elderly people more often choose bus when they do errands than younger people.

CPASCHM is an alternative specific constant for car passengers, for men with income higher than the average net income of DKK 128.750. CPASCLM is an alternative specific constant for car passengers, for men with income lower than the average net income of DKK 128.750. Men are less likely to be car passengers than women and the effect is more pronounced among men with a high income.

3.3.6 Structural coefficients

The structural parameters for those sub-models where a tree structure has been estimated, are shown below. The parameters are significantly different from 1 and thus the introduction of a tree structure improves the models.

Table 3-18. Structural coefficients, t-values in parentheses

Model Parameter Model	Mode pl
12	
12x	0.5006 (11.3)
13	0.4693 (13.3)
14	
214	0.2504 (11.2)
314	
cx13	
123	0.3158 (12.8)
23x	0.3083 (10.6)
24x	0.4999 (5.8)
134	0.2052 (11.7)

t-values given w.r.t. 1

3.4 Model validation

3.4.1 Value of time

VoTs are in principle transferable, but in practice depend on the specification of costs and the model. The following VoTs were found in the Stockholm model ([10]).

Table 3-19. VoT in the Stockholm mode, 1992 SEK per hour

Trip type	VoT
Work	20
School	16
Business, car	103
Business, PT	128
Shopping, brief daily Shopping trips	24
Other shopping	20
Visit, service and sport	15
Restaurant and culture	25

These VoTs are generally much smaller than the ones found here.

3.4.2 Selection bias

The following table shows the estimated VoT for each chain in the TDM, together with averages for selected variables that are considered to be correlated with the individual VoT. The objective is to check whether the differences in VoT, between different tour types, can be due to selection biases

The tour type sub-models concern both the main and the minor tour in chains consisting of two tours, and VoTs for both are provided in the following table.

Table 3-20. Socio-demographic variables, average by chain

Tour type	VoT, main tour	VoT, minor tour	Share of women	Income	Working time	Age	Cars in HH
0			52%	4.8	21.6	47.6	0.9
12	99		39%	5.6	34.1	38.4	1.0
13	68		56%	4.7	18.4	47.1	0.9
14	120		52%	4.7	20.3	43.9	0.9
123	33		58%	5.7	34.5	38.6	1.0
124	78		49%	4.8	29.2	33.0	0.9
134	111		57%	4.6	18.4	42.3	1.0
1213	83	60	45%	5.4	32.3	38.2	1.0
1214	83	69	40%	5.0	29.9	34.5	1.0
12313	27	60	64%	5.5	32.4	38.1	1.0
12314	27	55	59%	5.5	32.7	36.5	1.0
12413	78	60	70%	5.3	34.2	34.5	1.1
12414	78	55	49%	4.5	29.8	32.1	0.9

The data reveal that women are generally more likely to do errands. A correlation between the share of women and the values of time is not evident. A correlation between income and the values of time is equally unclear. Income and average weekly working time are of course closely linked, and IPs having chosen a chain involving work have generally higher income and working time.

The average age tends to be higher for IPs who did not go to work and lower for those who travelled for a leisure purpose. There may be some tendency for the values of time to be higher for those chains where the average age is high. The average number of cars does not vary much across chains.

There is probably a selection bias in the data, but it cannot be explained by sex, income, etc., which implies that the potential problem cannot be solved.

3.4.3 Model forecast

The estimated models must be able to predict behaviour close to the actual observed behaviour.

Table 3-21 provides the model prediction of number of trips by mode and tour type. A comparison with the actual figures in Table 3-2 shows that the model's prediction of the numbers of tours by mode, is very close to the observed distribution. Generally, the deviation is less than 1%. This was expected as all of the models include alternative specific constants.

Table 3-21. Number of tours by mode and tour type

Tour type	Walk, bicycle	Car	CP	Bus	Train
12	27.3%	50.2%	7.9%	11.9%	2.8%
12x	35.7%	46.6%	7.9%	8.0%	1.9%
13	31.2%	50.1%	10.8%	7.2%	0.7%
14	29.9%	41.5%	21.9%	5.8%	0.9%
214	34.7%	46.3%	13.4%	5.1%	0.5%
314	28.8%	50.9%	16.7%	3.3%	0.3%
cx13	34.5%	57.8%	6.1%	1.4%	0.2%
123	19.8%	62.9%	7.1%	9.1%	1.0%
23x	26.9%	61.3%	5.6%	4.9%	1.3%
24x	25.8%	48.4%	10.4%	13.1%	2.4%
134	15.5%	55.8%	20.0%	6.6%	2.2%
Total	30.0%	49.4%	12.0%	7.3%	1.3%

Table 3-22 shows the expected distances from the data material which forms the basis of the estimations of the models. Table 3-23 shows predicted kilometre, by mode and chain in the initial situation.

Table 3-22. Observed distances by model and mode

Model	Slow	Car	CP	Bus	Train	Total
12	1.8	20.9	2.6	4.8	2.2	32.3
12x	2.2	15.3	2.1	2.7	1.4	23.7
13	1.2	11.8	2.9	1.5	0.5	17.9
14	1.5	18.3	10.4	2.8	1.0	34.1
214	1.9	11.1	3.8	1.5	0.4	18.7
314	1.3	10.3	3.7	0.5	0.1	16.0
cx13	1.2	9.1	1.7	0.3	0.1	12.4
123	1.6	24.0	2.1	3.8	0.6	32.2
23x	2.0	19.1	1.3	2.0	1.1	25.5
24x	2.5	25.9	4.8	7.3	2.0	42.6
134	1.1	25.0	12.0	3.0	1.7	42.8
Average	1.68	17.36	4.30	2.75	1.03	27.11

Table 3-23. Forecast of distances by model and mode, initial situation

Model	Slow	Car	CP	Bus	Train	Total
12	2.21	24.88	2.44	3.24	1.14	33.90
12x	2.46	17.94	1.92	1.76	0.55	24.63
13	1.34	12.01	2.91	1.42	0.18	17.87
14	1.91	19.95	10.30	1.54	0.36	34.07
214	2.12	12.12	3.99	1.07	0.40	19.70
314	1.34	10.50	3.96	0.63	0.24	16.66
cx13	1.31	9.45	1.59	0.25	0.15	12.75
123	2.14	24.33	2.34	2.74	0.34	31.89
23x	2.42	19.49	1.14	1.39	0.35	24.78
24x	3.64	27.93	4.73	4.86	0.75	41.91
134	1.59	26.10	10.61	2.89	0.57	41.76
Average	2.04	18.61	4.18	1.98	0.46	27.27

A comparison of the actual distances with the model forecast, reveals that the models predict a total amount of travelled km close to the actual amount of travelled km. The models predict 27.27 km, while the actual travelled distance averages to 27.11 km. The average covers a variation over the different models of ± 5%.

However, there are some systematic differences in the distribution on modes. In general, the models predict too many slow kilometres and car kilometres and too few kilometres with public transport.

3.4.4 Sensitivity Analysis

Table 3-24 shows model predictions with an increase in petrol price from 5.92 to 12.00 DDK per litre (102.7%)

Table 3-24. Forecast of distances by model and mode, petrol price increased from 5.92 to 12.00 DKK per litre

Model	Slow	Car	CP	Bus	Train	Total
12	2.44	18.75	2.39	3.62	1.48	28.69
12x	2.64	13.41	1.80	1.89	0.63	20.37
13	1.39	10.30	2.72	1.48	0.19	16.09
14	2.05	16.12	9.67	1.67	0.42	29.93
214	2.21	9.13	3.37	1.11	0.42	16.23
314	1.58	7.05	3.59	0.78	0.35	13.36
cx13	1.52	6.88	1.37	0.31	0.21	10.29
123	2.57	14.69	2.14	3.37	0.53	23.30
23x	3.06	10.23	1.04	1.80	0.51	16.64
24x	3.92	20.73	4.46	5.38	0.95	35.44
134	1.66	21.14	9.45	3.05	0.62	35.91
Average	2.28	13.50	3.82	2.22	0.57	22.39

The increase in petrol price causes a reduction in average car kilometres from 18.61 to 13.50. Overall, the increased cost reduces the total travelled kilometres from 27.27 kilometres to 22.39 kilometres.

Furthermore, it appears that there is little substitution to other modes from car.

Table 3-25 shows the elasticities calculated from the scenario with a price increase to DDK 12.00 per litre.

The overall elasticity for car kilometres is calculated to -0.27, which is consistent with other studies. The elasticity for distance as car passenger is calculated to be –0.08, much lower than the elasticity for car drivers. This makes good sense, since the increased petrol price increases the incentive to drive more people in the same car.

Table 3-25. Price elasticity of travelled kilometre with regard to petrol price

Model	Slow	Car	CP	Bus	Train	Total
12	0.10	-0.24	-0.02	0.12	0.30	-0.15
12x	0.07	-0.25	-0.06	0.07	0.14	-0.17
13	0.03	-0.14	-0.06	0.04	0.06	-0.10
14	0.07	-0.19	-0.06	0.08	0.15	-0.12
214	0.04	-0.24	-0.15	0.03	0.04	-0.17
314	0.18	-0.32	-0.09	0.24	0.44	-0.19
cx13	0.16	-0.26	-0.13	0.21	0.37	-0.19
123	0.19	-0.39	-0.08	0.22	0.53	-0.26
23x	0.26	-0.46	-0.09	0.29	0.43	-0.32
24x	0.08	-0.25	-0.06	0.10	0.25	-0.15
134	0.04	-0.19	-0.11	0.05	0.08	-0.14
Average	0.11	-0.27	-0.08	0.12	0.24	-0.17

It could even be asserted that that the elasticity for car passenger could be positive, but it must be remembered that it takes a car driver to convey a car passenger. When car driving is reduced generally, there are less possibilities for a person to be car passenger. The negative elasticity indicates that the last mentioned effect outweighs the incentive to carry more people in the same car.

The figures reported in Table 3-25 are very similar to the TØI results from Norway. TØI [14] reports an elasticity of car kilometres with regard to direct car cost of -0.20 in the short/medium rum and 0.48 in the long run. The elasticity of total kilometres of all modes is reported to be -0.13 in the short run, and -0.22 in the long run.

3.4.5 Discussion

The results have indicated that generally the models predict distances that deviate substantially from the actually observed distances, i.e. the models appear to be unsuited to predict absolute travel distances measures (at least not without calibration of the models).

Alternatively, the models can be used to calculate relative changes or elasticities. The absolute distance measures can be calculated by applying the model prediction of changes to the actually observed situation initially.

PT LoS is not good, not surprising since we do not have PT network as such in model. PT network data is a scope for improvement of the models

Conclude on VoT, variable cost influence

One significant factor for a number of the models, is that their reliability would be enhanced through greater data input. This is especially so for the tour type models which include a detour, and are based on relatively few observations.

In addition, and possibly more importantly, there are generally few observations where the individuals choose train as the main mode. Therefore, it was necessary to treat bus and train as one mode in some of the models. The result of this simplification is that the models are not well suited to predict demand for train transport.

4 Chain Choice

This chapter details the chain choice model, which is the part of the TDM that predicts which activities the individuals will undertake, and what travel chain will be employed during a day.

The model can be thought of as a generalisation of the traditional frequency model, with the additional advantage that trip chaining, and the interaction between different travel purposes, are explicitly modelled.

Given the differences in mode choice and tour length across tour types, it is seen that a change in choice of travel chain will induce significant changes in the kilometres travelled by different modes. Thus, it is important to be able to determine how individuals choose a travel chain.

This chapter contains the following sections. Section 4.1 describes the data employed for the model and section 4.2 describes the model. Section 4.3 gives the estimation results and a validation of the model is given in section 4.4.

4.1 Estimation Data

Observations are weighted to individual level as described in [1].

The alternatives in the chain choice model are listed in the following table, along with the number of observations by chain. Some alternatives have only limited observations, but generally the observations are well dispersed over the alternatives.

Table 4-1. Alternatives in the chain choice model

Chain	Number of observations, weighted	Share
12	2238.4	16.5%
123	635.6	4.7%
1213	749.9	5.5%
12313	190.8	1.4%
124	321.9	2.4%
1214	1103.2	8.1%
12414	73.3	0.5%
12314	265.3	2.0%
12413	32.5	0.2%
13	2148.7	15.9%
14	2713.3	20.0%
134	445.5	3.3%
Home	2630.1	19.4%

Table 3-2 gives the number of tours by mode and tour type.

4.1.1 Logsums

The basis for the model is the link with the underlying mode and destination choice sub-models. It is through these links, that changes in, e.g., travel costs affect the choice of travel chain.

The logsums from the sub-models measure accessibility for tours with various purposes. The choice of travel chain is affected by accessibility such that, e.g., individuals with poor accessibility are more likely to stay at home.

Logsum transformation

Logsums may be thought of as being in units of utilities. These utilities are not comparable across models, since the scale of the model parameters is determined by the variance of the error terms which may differ across models. Therefore, the accessibility measures are transformed to monetary units.

For the models without nest structure, this is done simply by dividing the accessibility measure by the parameter for monetary costs from the sub-model. For the models with nest structure the accessibility measure is further divided by the structural parameter. We denote logsums transformed to monetary units by logsum(*), where * is the sub-model from which the logsum is computed and defined:

ArbLS = logsum(ch12) + logsum(c12x)
ShopLS = logsum(ch13) + logsum(ch14) + logsum(c134)

These are the main accessibility measures used in the model.

The initial formulation of the model employed all the logsums, and applied each to the chain alternative with which the corresponding sub-model is associated. Correlation between the logsums resulted in problems that are avoided with the current formulation.

4.2 Model Structure

The table below illustrates the assignment of parameters to alternatives and variables in the chain choice model.

Abbreviations

A number of abbreviations are employed and are listed below

- M - male
- F - female
- Hv - weekday
- We - weekend

- Ar - unemployed
- Jo - employed
- La - farmer and assisting wife
- Se - self-employed
- St - student

- Aux - auxiliary household
- Ch - at least one child in household
- d2 - age in years

The table should be read in the following way; each column corresponds to an alternative and each row corresponds to a variable. The cells indicate parameters such that, e.g., the parameter p20 is assigned to the alternative specific constant in the alternative for chain 123. The parameters are discussed with the estimation results.

Table 4-2. Variables in the Chain Choice Model

Chain	12	123	1213	12313	124	1214	12414	12314	12413	13	14	134	Home
Constant		p20	p30	p40	p50	p60	p70	p80	p90	p100	p110	p120	
St	p11												
M*Hv	p12												
F*Hv	p13												
ShopLS*(1-St)*Hv								p310	p310				
ShopLS*Ar*Hv		p311	p311	p311									
ShopLS*Jo*Hv		p312	p312	p312									
ShopLS*La*Hv		p313	p313	p313									
ShopLS*Se*Hv		p314	p314	p314									
ShopLS*St*Hv		p315	p315	p315									
ShopLS*Hv										p321			
ShopLS*We										p322			
(ch13LS+ch14LS)*Hv												p323	
(ch13LS+ch14LS)*We												p324	
Ch14LS					p326						p325		
Aux		p401	p401	p401				p401		p402			
F*Hv*Ch		p403		p403		p404		p403		p403			
Hv*(F-M)										p406			
(d2>66)*Hv													p407
Sunday*M										p408			
Sunday*F										p409			
Friday*M	p410												
Friday*F	p411												
Saturday													p412
d2													p413
d2*Hv*M	p414												
d2*Hv*F	p415												
Hv*Ar	p201	p201	p201	p201	p201	p201	p201	p201	p201	p155	p113	p155	
Hv*Jo	p202	p202, p151	p202, p151	p202, p151	p202	p202	p202	p202	p202				
Hv*La	p203	p203	p203	p203	p203	p203	p203	p203	p203				
Hv*Se	p204	p204	p204	p204	p204	p204	p204	p204	p204				
Hv*St	p205	p205	p205	p205	p205	p205	p205	p205	p205	p154		p154	
We*Ar	p206	p206	p206	p206	p206	p206	p206	p206	p206		p112		
We*Jo	p207	p207, p152	p207, p152	p207, p152	p207	p207	p207	p207	p207	p153		p153	
We*La	p208	p208	p208	p208	p208	p208	p208	p208	p208				
We*Se	p209	p209	p209	p209	p209	p209	p209	p209	p209				
We*St	p210	p210	p210	p210	p210	p210	p210	p210	p210		p111		
d2*Ar	p211	p211	p211	p211	p211	p211	p211	p211	p211				
d2*Jo*Hv	p212	p212	p212	p212	p212	p212	p212	p212	p212				
d2*St	p213	p213	p213	p213	p213	p213	p213	p213	p213				
Hv*Ar*ArbLS	p301	p301	p301	p301	p301	p301	p301	p301	p301				
Hv*Jo*ArbLS	p302	p302	p302	p302	p302	p302	p302	p302	p302				
Hv*La*ArbLS	p303	p303	p303	p303	p303	p303	p303	p303	p303				
Hv*Se*ArbLS	p304	p304	p304	p304	p304	p304	p304	p304	p304				
Hv*St*ArbLS	p305	p305	p305	p305	p305	p305	p305	p305	p305				

Like the mode and destination choice submodels, the chain choice model has been formulated such as to avoid illogical variation in the logsums. The issue is discussed on page 6.

No nest structure has been found that significantly improves model fit, and thus the complication of employing one has been avoided.

4.3 Estimation Results

Table 4-3 below gives summary statistics for the estimation of the chain choice model. There is no absolute scale for assessing the degree of fit as expressed by the Rho^2 values, but the values obtained are found to be satisfactory.

Table 4-3. Summary statistics

Observations	13544
Likelihood at zero	-34751
Likelihood w.r.t. constants	-28703
Final likelihood	-24437
Rho^2(Constants)	0.15
Rho^2(0)	0.30

Table 4-4 gives the parameter estimates.

Table 4-4. Parameter estimates

Parameter	Name	Estimate	T-value	Parameter	Name	Estimate	T-value
11	c12St	-0.39209	-4.3	301	HvArArbLS	1.23E-03	2.0
12	c12HvM	-0.26649	-1.7	302	HvJoArbLS	8.48E-04	3.2
13	c12HvF	-0.31746	-1.8	303	HvLaArbLS	4.68E-03	3.3
20	C123	-2.63895	-13.3	304	HvSeArbLS	2.68E-03	4.0
30	C1213	-2.31082	-11.7	305	HvStArbLS	0	N/A
40	C12313	-3.84243	-18.5	310	HvWSLLS	9.42E-04	5.9
50	C124	-3.24525	-9.2	311	HvArSLS	2.10E-03	7.8
60	C1214	-0.57854	-5.5	312	HvJoSLS	5.21E-04	3.1
70	C12414	-3.35841	-21.6	313	HvLaSLS	1.95E-03	4.4
80	C12314	-2.77412	-16.9	314	HvSeSLS	1.33E-03	5.8
90	C12413	-4.77801	-20.8	315	HvStSLS	1.26E-03	5.1
100	C13	-0.41505	-3.2	321	ShopHvLS	7.35E-04	6.0
110	C14	-0.38355	-2.3	322	ShopWeLS	4.59E-04	3.4
111	LeisWeSt	0.200209	1.8	323	134lsHv	2.01E-03	7.0
112	LeisWeAr	0.398248	4.9	324	134lsWe	1.39E-03	4.7
113	LeisHvAr	-0.16866	-2.3	325	14ls	9.82E-04	4.0
120	C134	-3.10771	-11.7	326	c124LS14	2.34E-03	4.2
151	WShopJoHv	1.124329	4.9	401	AuxWS	-0.85251	-6.8
152	WShopJoWe	0.382253	1.5	402	AuxS	-0.56391	-4.5
153	SLJobWe	0.565962	7.8	403	123FchHv	0.625014	10.2
154	SLSelvHv	-0.64384	-4.2	404	1214FchHv	-0.45676	-4.5
155	SLArblsHv	0.750879	9.4	406	13HvM-F	6.91E-02	2.1
201	WorkHvAr	-0.81639	-1.3	407	0PensHv	0.118236	1.2
202	WorkHvJo	1.061313	3.7	408	13SonM	-0.93407	-7.7
203	WorkHvLa	-5.10115	-4.0	409	13SonF	-1.54374	-10.3
204	WorkHvSe	-2.15462	-3.4	410	12FreM	-0.4269	-4.7
205	WorkHvSt	2.703114	10.8	411	12FreF	-0.74323	-6.0
206	WorkWeAr	-1.95123	-4.6	412	0Lor	-0.63108	-8.6
207	WorkWeJo	-1.01885	-8.5	413	0Age	1.34E-02	7.2
208	WorkWeLa	-2.26561	-4.3	414	12AgeHvM	1.84E-02	6.1
209	WorkWeSe	-0.55025	-2.9	415	12AgeHvF	1.07E-02	3.0
210	WorkWeSt	-0.22758	-0.9				
211	WorkAgeAr	-4.67E-02	-9.5				
212	WAgeJoHv	-7.86E-03	-2.5				
213	WorkAgeSt	-3.96E-02	-4.4				

The table is divided into sections to provide a better overview. The estimates are discussed in the following paragraphs.

Work common

Parameters 201 through 213 and 301 through 305 are common to all alternatives, including work. The first ten are constants for the population divided into week-day (Hv) and weekend (We) observations and the 5 occupation categories.

There are significant differences in the propensities to choose a work alternative, both between occupation categories and types of day. Generally, the likelihood of going to work is higher on weekdays, for students and for the employed.

Parameter 211 corresponds to age for unemployed, parameter 212 corresponds to age for employed people on weekdays and parameter 212 corresponds to age for students. The likelihood of going to work decreases with age for all three groups.

ArbLS is the logsums from sub-models ch12 and c12x added together, after been transformed to commensurate monetary units. A parameter is estimated for this measure on weekdays, separately for the five occupation categories. The measure was not significant on weekends.

The logsum parameters are of considerable importance for the models, since it is through these that changes in accessibility, derived from the mode and destination choice sub-models, affect chain choice. The a priori expectation is that all these parameters should be positive.

In the case of students, the parameter came out negative and insignificant, and it is constrained to zero. Otherwise, the parameters are significant with the expected sign. Thus, the likelihood of choosing a chain including work increases with the accessibility to work destinations.

Constants

Parameters 20, 30, ..., 120 are alternative specific constants for all alternatives. This excludes the stay home alternative which is taken as the base and chain 12 which is taken as the base for the work alternatives. The work alternatives already have a common constant since p201 to p210 sum to 1.

Parameters 11, 12 and 13 show decreased likelihood for chain 12 for students, and men and women on weekdays. The likelihood of going to work on weekdays is only smaller than the likelihood of going to work and doing something else, particularly for students.

Parameters 111, 112 and 113 show increased likelihood for chain 14 for students and unemployed on weekends, and decreased likelihood for unemployed on weekdays.

Parameters 151 and 152 show increased likelihood for employed to both do errands and go to work (chains 123, 1213 and 12313) on weekdays and weekends.

Parameters 153, 154 and 155 concern chains 13 and 134 and show increased likelihood for employed on weekends, decreased likelihood for self-employed on weekdays and increased likelihood for unemployed on weekdays.

More logsums

Parameters 310 through 325 are more parameters applied to logsum measures. ShopLS is the sum of the logsums from sub-models ch13, ch14 and c134.

Parameter 310 is applied to ShopLS on alternatives 12314 and 12413 on weekdays for all except students and is quite significant.

Parameters 311 through 315 are applied to alternatives 123, 1213 and 12313 for the five occupation categories.

Parameters 321 and 322 are applied to chain 13 and shopLS for weekdays and weekends and parameters 323 and 324 are applied to chain 134 for weekdays and weekends with the sum of the logsums for sub-models ch13 and ch14.

Parameter 325 is applied to alternative 14 for all with the logsum for sub-model ch14. Parameter 326 is applied to alternative 124 also with the logsum for sub-model ch14. For alternatives 1214 and 12414 no logsum parameter could be estimated to be significant with the right sign.

Miscellaneous parameters

The last set of parameters have been included, after the parameters described above were accepted into the model. As a rule, parameters have only been included when they could contribute significantly to improving the fit of the model. Thus, a number of parameters that would have yielded a t-value of two, and thus be significant, have been left out. However, in some cases parameters that were significant on entry have become insignificant after inclusion of more variables. These variables have generally been retained in the model, unless the sign subsequently differed from a priori expectations. This has not actually been the case for any variable.

Parameter 401 shows that ancillary households, i.e. adults living with their parents, are less likely to go both to work and undertake errands. Parameter 402 show that they are also less likely to undertake errands only. Perhaps their parents do the shopping.

Women with children are more likely to choose chain 123 on weekdays (p403) and less likely to choose chain 1214 (p404). Thus women with children tend to do the errands (or pick up children, etc.), and tend not to have leisure activities in the evening. A similar effect was not significant for men.

Parameter 406 is treated such that it is positive for women and negative for men. Thus, women are more likely to do errands on weekdays while men are less likely.

Pensioners are defined to be people older than 67 and they are more likely to stay at home on weekdays (p407). The parameter became insignificant when parameter 413 showing the likelihood of staying at home to increase with age was included but is left in.

Parameters 408 and 409 show decreased likelihood to do errands only, chain 13, on Sundays for men and women. The likelihood decreases most for women.

Parameters 410 and 411 show that the likelihood of going to work only, chain 12, on Fridays decreases for men and women. The likelihood again decreases most for women.

The likelihood of staying at home is lower on Saturdays and increases (on all days) with age, (p412 and p413).

The likelihood of going to work only on weekdays increases with age for both men and women, most for men, (p414 and p415).

General

All parameters have the expected sign. Parameters with the wrong sign would not have been included in the model.

The logsum parameters are generally well significant. Dummies, mainly parameters 401 through 415, are only included when they contribute significantly to improve the model fit and have an intuitive interpretation. More variables could have been added, but were omitted to prevent undue complexity in the model.

4.4 Model Validation

The following table illustrates actual choices by type of day and type of occupation, and also provides the deviations of the base model predictions from actual choices. The deviations are small and do not justify the inclusion of more parameters.

Tables like the following, for all available variables have been used to search for variables for inclusion. There are no major deviations left between actual choices and the base forecast, that justify the inclusion of more variables unless one is willing to loosen the requirement of how much new variables should improve model fit.

Table 4-5. Actual and base forecast by day and occupation

	Weekdays					Weekends				
Choice	Unemp	Emp	Farmer	Self-emp	Student	Unemp	Emp	Farmer	Self-emp	Student
ch12	56.6	1511.2	15.2	129.9	327.3	2.7	135.3	1.1	29.1	30
Dev.	5.1	4.0	-0.2	-8.5	-0.6	1.2	0.5	0.9	-3.1	0.6
ch123	27.2	495.1	6	35	60.6	0	10.6	0	1	0
Dev.	-6.0	-9.6	-1.6	-13.1	23.6	0.3	2.9	0.1	0.8	2.6
ch1213	19.7	554.3	3.2	18.9	121.1	1.8	22.3	1.7	4.5	2.2
Dev.	5.5	11.6	2.5	9.2	-21.6	-1.4	-3.5	-1.5	-1.9	1.4
ch12313	8.5	147.7	1.6	4.3	23.2	0	3.4	0	2	0
Dev.	-2.1	-2.0	-0.3	2.3	2.1	0.1	0.7	0.0	-1.4	0.8
ch124	7.2	176.1	1.4	10.9	92.6	1.6	14.5	0	4.4	13.4
Dev.	0.2	16.4	0.2	1.9	-17.3	-1.0	6.4	0.3	-0.3	-6.9
ch1214	26.5	658.7	4.8	38	258.7	1.5	80.2	1.1	10.2	23.4
Dev.	-1.7	-19.2	0.8	5.2	12.0	0.7	-4.0	0.0	4.4	2.0
ch12414	1.4	41.2	1.1	2	21.7	0	3.9	0	1.1	0.9
Dev.	0.3	1.9	-0.7	0.8	-3.7	0.1	0.8	0.1	-0.2	0.7
ch12314	9	202.9	2.5	11.2	28.6	0	8.8	0	0	2.2
Dev.	-2.1	-3.3	-0.9	1.8	3.4	0.2	-0.7	0.1	1.6	0.0
ch12413	0	23.4	0	1.1	2.4	0	4.2	0	0	1.4
Dev.	0.8	0.2	0.2	0.5	2.0	0.0	-3.1	0.0	0.2	-1.0
ch13	924.9	403	50.9	40.6	82.7	155.2	403.3	7.6	27.8	52.7
Dev.	-0.5	-8.7	-9.2	-0.4	14.2	-14.0	-3.7	5.4	3.0	13.9
ch14	732.6	323.7	33.2	38.6	105.3	412.4	791.1	26.5	58.5	191.4
Dev.	0.0	4.7	4.2	-2.1	-5.9	0.0	7.4	-4.7	-3.5	0.0
ch134	177.9	75.1	5	5.2	19.9	28.4	104	0	5.5	24.6
Dev.	0.6	-4.5	1.8	2.4	-0.1	5.3	-3.7	2.5	1.6	-6.1
Home	778.1	461.2	63.2	109.7	123.5	358.4	494.6	30.4	65.6	145.5
Dev.	0.0	8.6	3.1	0.0	-8.3	8.6	0.0	-3.1	-1.2	-7.8

The deviations between actual choices and base forecasts sum to zero for each alternative, since the model includes a full set of alternative constants.

4.4.1 Sensitivity Analysis

In the following tables, we investigate how the chain choice model predicts a change in choice of travel pattern and chain, when all logsums are decreased, corresponding e.g. to an increase in petrol cost. Such a change would also affect mode and destination choice, but this change is not shown here.

The investigated change is quite substantial and corresponds to all destinations being moved a distance that would increase the cost of access by 100 DKK. The lengths of each of the tours differs in the sub-models, so that the assumed change does not correspond to a change in, e.g., the price of petrol.

Table 4-6. Base forecast versus decreased logsums

Choice	Weekdays					Weekends					Total
	Unemp	Emp	Farmer	Self-emp	Student	Unemp	Emp	Farmer	Self-emp	Student	
ch12	61.7	1515.2	15	121.4	326.7	3.9	135.8	2	26	30.6	2238.3
Change	-5.3	55.6	-7.2	-18.8	31.8	0.3	10.9	0.1	1.5	2.1	71
ch123	21.2	485.5	4.4	21.9	84.2	0.3	13.5	0.1	1.8	2.6	635.5
Change	-10.7	-52.0	-3.1	-9.3	-19.9	0.0	1.1	0.0	0.2	0.2	-93.5
ch1213	25.2	565.9	5.7	28.1	99.5	0.4	18.8	0.2	2.6	3.6	750
Change	-12.8	-62.0	-4.0	-11.8	-23.9	0.0	1.5	0.0	0.1	0.2	-112.7
ch12313	6.4	145.7	1.3	6.6	25.3	0.1	4.1	0	0.6	0.8	190.9
Change	-3.3	-15.6	-0.9	-2.8	-6.0	0.0	0.3	0.0	0.0	0.0	-28.3
ch124	7.4	192.5	1.6	12.8	75.3	0.6	20.9	0.3	4.1	6.5	322
Change	-2.0	-33.9	-0.9	-4.1	-9.7	-0.1	-3.0	-0.1	-0.6	-1.0	-55.4
ch1214	24.8	639.5	5.6	43.2	270.7	2.2	76.2	1.1	14.6	25.4	1103.3
Change	-2.0	24.0	-2.7	-6.8	26.0	0.1	6.1	0.1	0.8	1.7	47.3
ch12414	1.7	43.1	0.4	2.8	18	0.1	4.7	0.1	0.9	1.6	73.4
Change	-0.2	1.6	-0.2	-0.5	1.8	0.0	0.4	0.0	0.1	0.1	3.1
ch12314	6.9	199.6	1.6	13	32	0.2	8.1	0.1	1.6	2.2	265.3
Change	-2.1	-42.5	-1.0	-4.6	3.5	0.0	0.6	0.0	0.1	0.2	-45.8
ch12413	0.8	23.6	0.2	1.6	4.4	0	1.1	0	0.2	0.4	32.3
Change	-0.2	-5.1	-0.1	-0.5	0.4	0.0	0.1	0.0	0.0	0.0	-5.4
ch13	924.4	394.3	41.7	40.2	96.9	141.2	399.6	13	30.8	66.6	2148.7
Change	-66.2	-3.3	0.3	5.5	-10.4	-8.1	-20.9	-0.8	-2.2	-4.0	-110.1
ch14	732.6	328.4	37.4	36.5	99.4	412.4	798.5	21.8	55	191.4	2713.4
Change	32.5	37.9	4.9	10.1	-0.1	-11.0	-16.4	-0.7	-2.1	-5.6	49.5
ch134	178.5	70.6	6.8	7.6	19.8	33.7	100.3	2.5	7.1	18.5	445.4
Change	-40.3	-12.3	-1.0	-0.3	-5.1	-6.3	-18.2	-0.5	-1.4	-3.5	-88.9
Home	778.1	469.8	66.3	109.7	115.2	367	494.6	27.3	64.4	137.7	2630.1
Change	112.5	107.4	15.9	43.9	11.7	25.0	37.5	1.7	3.6	9.2	368.4

The chains that involving both errands and work decrease most. The number of persons staying at home increases 14% from 19.4% of the total to 22.1%. Students and employed are least likely to stay at home, and least likely on weekdays. The increase in the likelihood of staying home is largest on weekdays for unemployed, farmers and self-employed.

The general tendency is that the likelihood of choosing all other chains decreases. The decrease is in the range 15-20% for chains involving work. For chain 13 it is -5.1%, and -20.0% for chain 134.

The exceptions are chain 12 (+3.2%), chain 1214 (+4.3%), chain 12414 (+4.2%) and chain 14 (+1.8%). These increases are on a much lower scale than the decreases otherwise seen.

That chain 12 is chosen more often can perhaps be justified if the change is interpreted such that people simplify their travel behaviour as a consequence of increased travel costs. Similarly, it could be true that the likelihood of choosing chain 14 increases when travel costs increase. A separate logsum parameter is found for chain 14, but it is found to be so small that the impact of logsums on the other alternatives outweighs the impact on chain 14. If reduced accessibility decreased the likelihood of choosing chain 14 in the data, then the effect would have been captured in the model.

The increase in chain 1214 could perhaps be acceptable. The chain is chosen in 8% of all observations and checks have been performed to see if a separate logsum parameter could be included. This is not the case.

It does not seem plausible that chain 12414 increases as the model shows. Again, it has been checked if a logsum parameter could be included. As the chain is chosen by less than 1% of observations, the overall consequences of the missing effect are negligible.

Except for chain 14 the increases are on weekdays for students and employed. For chain 14 the increases are on weekdays for all occupations except students.

The next table shows the number of tours for the groups, these are defined to be the number of times a person leaves home. The number of tours decreases for all categories. Most on weekdays, for farmers and self-employed who may be more flexible. Least for employed and students who must go to work. The overall decrease in the number of tours is 3.8%

Table 4-7. Number of tours, base forecast versus decreased logsums

	Weekdays					Weekends					Total
	Unemp	Emp	Farmer	Self-emp	Student	Unemp	Emp	Farmer	Self-emp	Student	
Base	2057.4	6221.3	136.5	431	1602.1	598.1	1695	42.7	165.8	384.2	13333.4
Changed	1924.2	6014.1	111.7	360.1	1592.3	573.1	1666	40.9	163.4	376.8	12823.9
% Change	-6.5%	-3.3%	-18.2%	-16.5%	-0.6%	-4.2%	-1.7%	-4.2%	-1.4%	-1.9%	-3.8%

The table below shows the number of tours for the three purposes. The number of errand tours decreases most, with decreases in the same range for the occupation groups and with highest decreases on weekdays. Errand tours seem to be most flexible.

Work tours on weekdays decrease most for farmers, unemployed and self-employed, least for employed and students. This is plausible, since employed and students have less flexibility in choosing when to work. On weekends there is a small increase in work tours for all groups.

Leisure tours are least flexible with small decreases generally, except for students on weekdays.

Table 4-8. Number of chains, base forecast versus decreased logsums

Including	Weekdays					Weekends					Total
	Unemp	Emp	Farmer	Self-emp	Student	Unemp	Emp	Farmer	Self-emp	Student	
Work, base	156.1	3810.6	35.8	251.4	936.1	7.8	283.2	3.9	52.4	73.7	5611.0
Changed	117.5	3680.7	15.7	192.2	940.1	8.1	301.2	4.0	54.6	77.2	5391.3
Errand, base	1163.4	1885.2	61.7	119.0	362.1	175.9	545.5	15.9	44.7	94.7	4468.1
Changed	1027.8	1692.4	51.9	95.2	300.7	161.5	510.0	14.6	41.5	87.8	3983.4
Leisure, base	952.7	1497.3	53.6	117.5	519.6	449.2	1009.8	25.9	83.5	246.0	4955.1
Changed	938.4	1467.0	52.6	110.8	536.4	431.9	979.4	24.7	80.4	237.9	4859.5
Changes in percent											
Work	-25%	-3%	-56%	-24%	-0%	4%	6%	3%	4%	5%	-4%
Errand	-12%	-10%	-16%	-20%	-17%	-8%	-7%	-8%	-7%	-7%	-11%
Leisure	-2%	-2%	-2%	-6%	3%	-4%	-3%	-5%	-4%	-3%	-2%

4.4.2 Conclusion

Tables like Table 4-5 clearly indicate that the possibilities for including further variables to significantly improve the model are remote. The model is relatively parsimonious, with high significance for most variables and a satisfactory fit. The signs and relative sizes of parameters have intuitive interpretations in most cases, or do not contradict intuition.

The sensitivity analysis illustrates that the model on the whole reacts as expected to a decrease in accessibility. The changes may be surprisingly small. However, there is no basis for comparison and hence no grounds to reject the model.

5 Car Availability

The model on the top level predicts car availability at the level of the household, rather than car ownership. This is a reflection of the information available in the TU data. The cost used is, however, the cost of car ownership.

The model distinguishes between single and two adult households, and in the following paragraphs, the latter are referred to as couples. See [1] for definitions of household types.

The main variables driving the model are accessibility measures derived from the chain choice model and income.

License holding is also considered to be an important variable, as the cohort model and the license holding model (see [2]) are used to incorporate time dependent cohort effects into the forecast of car availability.

5.1 Estimation Data

Weights

Weights have been calculated to correct the TU sample for skewness in the sampling procedure. Since large households have a higher probability of being sampled, it is required to have a set of weights for the household level as well as for the individual IP level. The calculation of weights is described in [6].

The car availability model concerns the household decision of car availability and therefore the set of weights corresponding to the household level is used.

Observed car availability

The number of single and two adult households in the sample with 0, 1, 2 and 3+ cars is shown in Table 5-1 below. Only few single adult households have two or more cars and few two adult or couple households have three or more cars. Thus, the car availability model only includes alternatives for 0 and 1+ cars for single adult households and 0, 1 and 2+ cars for couples.

Table 5-1. Observed distribution of cars in households

Cars	Single	Two adult
0	1733	1217
1	1196	7381
2	65	1762
3+	13	178

(Figures not corrected for weight.)

Income and prices

The income measure employed in the model is net income after taxes for the two persons defined as head of household and partner. The cost of having a car available is taken to be DKK 25000 per year.

5.1.1 Accessibility measure

The logsum from the chain choice model expresses the accessibility to the chain choice alternatives as a whole. One of the alternatives is to stay home, which should not affect car availability.

Alogit can output the logsum which can be written

$$\log\left(\sum_i e^{U_i}\right)$$

and also the probability of staying home, P_H, which can be rewritten

$$\log(1-P_H) = \log(\sum_{i \neq H} e^{U_i}) - \log(\sum_i e^{U_i}).$$

Thus,

$$\log\left(\sum_i e^{U_i}\right) + \log(1-P_H) = \log(\sum_{i \neq H} e^{U_i}),$$

expressing the accessibility to all chains other than staying home, can be computed using standard Alogit output. This accessibility measure has been tested in the car availability model

However, it was found that the measure did not perform very well, and the expected number of car kilometres has been used.

Generation of accessibility measure

The mode and destination choice models and the chain choice models are run three times each, with socio-demographic variables describing the head of the household as defined ([1]). The runs assume that the household has none, one or two cars and expected car kilometres and logsums are computed as indicated above for each of the cases.

In the final estimation results shown, the expected car kilometres given car ownership are used to explain car availability. If the head of household is expected to travel a lot by car, it is expected that the likelihood of the household having a car available increases.

5.1.2 Urbanisation variable

The model employs an urbanisation variable for the residence of the HP which has the following coding.

URBAN	Definition
11	Copenhagen, except
12	Frederiksberg
20	Other Cph suburbs
30	>100,000 inhabitants
41	>70,000 inhabitants
42-43	22-60,000 inhabitants
44	10-22,000 inhabitants
50	2-10,000 inhabitants
60	200-2000 inhabitants
70	Rural areas

5.2 Model Structure

5.2.1 Utility functions

With only five alternatives in the model, it becomes feasible to write the utility functions out in full. They are given below together with brief explanations of the variables.

The alternatives are defined such that alternative 1 and 2 are 0 and 1+ cars and available for singles. Alternatives 4, 5 and 6 are available for couples and are 0, 1 and 2+ cars, respectively.

U1 = p111*KMO	accessibility with no car
+ p115*ifeq(d10+d22,0)	no licence
+ p120*ifeq(d15,3)	long education
+ p1*ifeq(d24,11)	Copenhagen
+ p2*ifeq(d24,12)	Frederiksberg
+ p3*ifeq(d24,20)	Greater Copenhagen
+ p4*ifeq(d24,30)	Other cities with more than 100000 inhabitants
+ p5*ifeq(d24,41)	
+ p6*ifeq(d24,42)	
+ p7*ifeq(d24,43)	
+ p8*ifeq(d24,44)	

+ p9*ifeq(d24,50)	
+ p10*ifeq(d24,60)	
U2 = p102	constant
+ p111*KM1	accessibility with one car
+ p112*(Income - CarFxCst)	remaining income
+ p114*d12	auxiliary person in household
U4 = p211*KM0	accessibility with no car
+ p216*ifeq(d10+d22,0)	no licence in household
+ p220*ifin(d16,1,2)	head is a student
+ p220*ifin(d20,1,2)	partner is a student
+ p221*ifeq(d15,3)	head has long education
+ p221*ifeq(d18,3)	partner has long education
+ p11*ifeq(d24,11)	
+ p12*ifeq(d24,12)	
+ p13*ifeq(d24,20)	
+ p14*ifeq(d24,30)	
+ p15*ifeq(d24,41)	
+ p16*ifeq(d24,42)	
+ p17*ifeq(d24,43)	
+ p18*ifeq(d24,44)	
+ p19*ifeq(d24,50)	
+ p20*ifeq(d24,60)	
U5 = p202	constant
+ p211*KM1	accessibility with one car
+ p212*(Income-CarFxCst)	remaining income
+ p215*ifeq(d10+d22,2)	both head and partner have licence
+ p21*ifeq(d24,11)	
+ p22*ifeq(d24,12)	
+ p23*ifeq(d24,20)	
+ p24*ifeq(d24,30)	
+ p25*ifeq(d24,41)	
+ p26*ifeq(d24,42)	
+ p27*ifeq(d24,43)	
+ p28*ifeq(d24,44)	
+ p29*ifeq(d24,50)	
+ p30*ifeq(d24,60)	

U6 = p203	constant
+ p211*KM2	accessibility with two cars
+ p212*(Income-2*CarFxCst)	remaining income
+ p213*(Income-2*CarFxCst)	remaining income
+ p214*d12	auxiliary person in household
+ p215*ifeq(d10+d22,2)	both head and partner have licence
+ p217*ifeq(d10+d22,1)	only one licence in household

Car fixed cost

The cost of owning a car does not vary across observations. This is a problem for the estimation of the influence on car prices on car availability. It would be more reassuring to be able to estimate a separate parameter for the fixed costs of car ownership (availability) rather than having to use the income parameter.

But variation in the costs of car availability cannot be obtained, except through use of time series data or cross country data, none of which are available in the form required for the TDM.

Variation between households in the actual cost of owning a car cannot be used, since all households in principle have access to buying the same (typical entry level) car. Individual household variation in costs reflect the car type decision where the quality of the car is traded off against the price. Car type choice is not modelled here, just the decision of whether to have a car.

5.3 Estimation Results

5.3.1 Stepwise estimation

There is a plausible correlation between fuel costs and car ownership, that has been identified during time-series work. The relationship between urbanisation and car availability suggests that an equally plausible correlation is that between the more general accessibility and car ownership. Therefore, accessibility is expected to enter the car availability model.

Household type, income, urbanisation and licence holdings explain much of the variation in car availability. However, it turns out that accessibility as measured by the logsum described on page 6 is not a particularly strong variable. The use of the logsum as an accessibility measure has the additional attraction that the whole TDM then can be viewed as one very large nested logit model with the theoretical properties of such models being readily available.

Instead the expected number of car kilometres for the head of household given car availability is used. In retrospect, expected car kilometres is a more obvious measure. Intuitively, expected car kilometres are more directly related to car ownership than the more abstract accessibility measure represented by the logsum.

The expected number of car kilometres is correlated with urbanisation, such that both the expected car kilometres and car availability increase with lower urbanisation. Urbanisation is also very good at explaining car availability.

Therefore a stepwise estimation procedure is employed. First the model is estimated without urbanisation variables. The parameters for expected car kilometres are fixed at the estimated values and the model is re-estimated including dummies for seven different urbanisation levels.

5.3.2 Results

Summary statistics for the estimation are shown in Table 5-2. The fit is satisfactory, as the figures indicate. The parameter estimates are presented in Table 5-3 below.

Table 5-2. Summary statistics

Observations	13545
Likelihood at zero	-12101
Likelihood w.r.t. constants	-10048
Final likelihood, step 1	-7778
Final likelihood, step 2	-7464
Rho^2(Constants)	0.26
Rho^2(0)	0.38

Table 5-3. Estimation results, t-values in parentheses

Parameter	Description	Alternative	Estimate	t-value
P102	ASC singles	2	0.560464	3.3
P111	Km singles	1, 2	1.85E-02	6.9
P112	Remaining income	2	1.33E-02	18.7
P114	Auxiliary in household	2	0.843338	8.3
P115	No licence	1	2.777057	22.5
P120	Education level is high[5]	1	0.609103	8.7
P202	ASC couples 1 car	5	1.475289	6.0
P203	ASC couples 2 cars	6	-0.87913	-3.4
P211	Km couples	4, 5, 6	2.85E-02	6.7
P212	Remaining income	5, 6	5.20E-03	7.1
P213	Remaining income	6	7.14E-03	16.8
P214	Auxiliary in household	6	0.681425	11.3
P215	Both have licence	5,6	1.160906	11.2
P216	No licence	4	3.736543	12.6
P217	Only one licence	6	-1.49019	-8.9
P220	Head or partner is a student (dummy is 2 if both)	4	1.008137	7.8
P221	Head or partner has skolud=3 (dummy is 2 if both)	4	0.721748	6.5

Generally, the estimated parameters are very significant and all have the expected sign. Indeed, with the high number of observations available, parameters were only allowed to enter the model if they could contribute significantly in terms of the likelihood.

The parameters for expected car kilometres from the models, lower in the TDM hierarchy, are of course very important, since it is through these that the changes in accessibility affect car availability. It will be of particular interest to analyse, e.g., the response of car availability to increased fuel prices.

The parameters are very significant, for couples the parameter is smaller. That the sensitivity to changes in accessibility is smaller for couples is perhaps not surprising. It takes less to make a couple buy a car.

Similarly, the sensitivity to income is smaller for couples. For couples, two income parameters are estimated with the sensitivity to income being higher for the 2+ car alternative than for the 0 and 1 car alternatives.

The parameters to the licence holding dummies imply an increased likelihood for not having a car for both singles and couples when there are no licences in the household. For couples where both have a license, the likelihood of having at

[5] SKOLUD=3, refer ?

least one car is increased, but if only one has a licence then the probability for having two cars is decreased. This conforms with a priori expectations.

Parameters 114 and 214 are dummies for when there is an auxiliary person in the household. In both single and couple households this increases the likelihood of having a car.

Parameters P120 and P221 imply that car availability is lower when skolud=3, i.e. when the HP has more than 12 years of formal education.

Finally for couples, a parameter is included indicating that car availability is lower if either head or partner is a student. If both are students the contribution of the parameter is doubled.

Table 5-4. Urbanisation variables

Parameter	Description	Alternative	Estimate	t-value
P1	Urb11	1	2.331878	13.5
P2	Urb12	1	0.76239	1.2
P3	Urb20	1	2.18326	11.8
P4	Urb30	1	2.10093	11.8
P5	Urb41	1	1.736465	5.4
P6	Urb42	1	1.941321	9.9
P7	Urb43	1	1.963597	10.1
P8	Urb44	1	1.744474	8.8
P9	Urb50	1	1.256946	7.1
P10	Urb60	1	1.178558	6.2
P11	Urb11	4	3.055649	11.2
P12	Urb12	4	4.445832	2.1
P13	Urb20	4	2.42637	8.6
P14	Urb30	4	2.530963	9.0
P15	Urb41	4	2.744507	4.8
P16	Urb42	4	2.146885	6.7
P17	Urb43	4	1.925901	5.9
P18	Urb44	4	2.020957	6.4
P19	Urb50	4	1.462306	5.4
P20	Urb60	4	0.583198	1.8
P21	Urb11	5	0.959807	6.5
P22	Urb12	5	2.712048	1.5
P23	Urb20	5	0.827545	6.1
P24	Urb30	5	0.915982	6.2
P25	Urb41	5	1.641915	3.9
P26	Urb42	5	0.823368	5.1
P27	Urb43	5	0.942759	5.7
P28	Urb44	5	0.685106	4.3
P29	Urb50	5	0.658129	6.1
P30	Urb60	5	0.311577	2.8

The urbanisation parameters imply that the probability of having a car available increases with decreasing urbanisation, that is car availability is higher in rural areas than in larger cities, in line with expectations.

5.4 Model Validation

5.4.1 Sensitivity analyses

The model is tested through a series of sensitivity analyses. These are summarised in Table 5-5. In the first scenario, income is increased by 10% for all, which leads to increased car availability. Next, the car price is increased by 10% leading to decreased car availability. Finally, in the last two columns, the expected car kilometres with one and two cars is increased by 10%, again leading to increased car availability. The expected car kilometres with no cars is increased by 10%, leading to decreased car availability.

In the table the number of cars is calculated assuming that single adult households with 1+ cars on average have 1.071 cars available and that two adult households with 2+ cars on average have 2.092 cars available. These figures are calculated from the TU data which are used for estimation.

Table 5-5. Sensitivity analyses

Scenario	Base	Income + 10%	Car price + 10%	Access with car + 10%	Access without car +10%
Single, 0 cars	3970.8	3811.6	4006	3931.7	3977.5
Single, 1+ cars	2862.2	3021.4	2827	2901.3	2855.5
Couple, 0 cars	756.9	702.9	764.9	738.8	760.7
Couple, 1 car	4718.1	4593	4752.1	4719.4	4714.8
Couple, 2+ cars	1236.6	1415.7	1194.6	1253.3	1236
Cars	10370	10791	10279	10449	10359
Elasticity		0.41	-0.09	0.08	-0.01

The income elasticity of car ownership is found to be 0.41, at 0.56 it is higher for singles. For couples, the number of households with 0 and 1 cars decreases while the number of 2 car households increases.

Similarly, the car price elasticity of -0.09 is higher, -0.12, for singles. The elasticities found for accessibility are also higher for singles. For the population as a whole the elasticity is 0.08 for expected car kilometres with cars and -0.01 for expected car kilometres without cars.

5.4.2 Discussion

The income elasticity found in the present analysis of cross-section data of 0.40 is lower than the elasticities found in time series analyses. In [11] it is concluded that the long term income elasticity of car ownership probably is around 0.8-0.9. This conclusion is based on some time series analyses of car ownership in Denmark.

There may be several explanations for this difference: First, the income variables are not directly comparable. The present model uses net income after taxes while the time series analyses use some aggregate form of real income. Secondly, there are issues with income distribution and cross-sectional versus longitudinal effects. Thirdly, there is an issue of spurious correlation which can be found in time series analyses.

As shown on the Cohort model there are significant cohort effects in licence holdings, and potentially in car ownership. The presence of cohort effects implies that car ownership has increased and will increase independently of income.

Jansson [13] argues that a diffusion process (a cohort effect) must account for a period in Sweden with declining income, increasing fuel prices and still increasing car ownership. He also shows that car ownership has been increasing at given income levels, i.e. car ownership increases independently of income.

Like car ownership, income has been increasing in the past. Thus, there is a danger that what might appear as an income effect in time series analyses, is really a combination of income and cohort effects. If this hypothesis is correct, then the real income elasticity is lower than the one revealed in the time series analyses.

Car ownership has been analysed in connection with the Norwegian National Model, ([14]). A joint ownership and use model, employing cross-sectional data, has revealed an income elasticity of 0.23.

Goodwin has reviewed a number of studies giving different demand elasticities with respect to fuel price. He states a likely range for the fuel price elasticity of car ownership of 0.15 to 0.30. This is considerable higher than what has been revealed by this model, although a detailed explanation might require the utilisation of further cross-sectional data.

6 Appendix

6.1 Bibliography

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6.2 List of Abbreviations

ASC	Alternative specific constant
CP	Car passenger
DMU	Danish Environmental Agency
DS	Danmarks Statistik, the Danish statistical bureau
GTC	Generalised travel cost
HH	Household
HP	Head of household as defined in [1]
IP	Interview person, the person for which the TU diary is made
LoS	Level of service in public transport
PT	Public transport
TDM	Travel demand model
TU	The travel diary survey underlying the TDM
VoT	Value of time