Value of Travel Time Savings

A study in the cross-mode variations of mixed logit estimates

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List of abbreviations

CE………………..Choice experiments

CV……………….Contingent Valuation

GLR……………...Generalized Likelihood Ratio

IIA……………….Independence of Irrelevant Alternatives

L…………………Alternative on the Left side of the respondent's screen (Refers always to the first alternative of the binary choice set)

LM……………… Lagrange Multiplier

LR………………..Likelihood Ratio

ML……………….Maximum Likelihood

MLE……………..Maximum Likelihood Estimate

MSL……………..Maximum Simulated Likelihood

NOK…………….Norwegian Kroner

pdf……………….Probability distribution function

R………………... Alternative on the Right side of the screen (Refers always to the second alternative of the binary choice set)

RP………………. Revealed Preference

RUM…………… Random Utility Model

SP………………. Stated Preference

TT……………….Travel time

VoT ……………...Value of time

VTT…………….. Value of Travel Time

VTTS…………… Value of Travel Time Savings

WTP…………….Willingness to Pay

0. Introduction

0.1 The value of travel time savings (VTTS)

The *value of travel time savings* (VTTS) is the monetary value attached to reductions in travelling time. "With some exception, travel is considered as an intermediate good. Hence it is the travel time savings that should constitute value" (Ramjerdi, 1993). Unfortunately there is neither a market, nor an observable price for time. Nevertheless, people are willing to pay for time savings; in most economic decisions time is present, at least in the background.

VTTS is an important *willingness-to-pay* (WTP) indicator which plays a crucial role in economic evaluation of transport projects and in pricing policies. 'In the UK for example, travel time savings have accounted for around 80% of the monetized benefits within the cost-benefit analysis of major road schemes' (Mackie et al., 2001). Practically, *behavioral values* of various types of travel time are obtained from travel demand models as an implicit trade off between money and travel time. VTTS is estimated from models of discrete choice as the *ratio of the marginal utility of time on the marginal utility of income*. For linear-in-parameters utility specifications this ratio is simply the ratio of time on price coefficient. There is a methodological debate on the legitimacy of discrete choice models to estimate VTTS and on their justification by economic theory (see Chapter 1).

Empirically, it is often the case that VTTS exhibits large variations with respect to many parameters rather than being homogeneous across them. These can be associated with the trip itself (*trip characteristics*, i.e. distance, purpose), the *type of user* or socioeconomic status of the traveler (e.g. income, age, family status etc.), the *attributes of the transport mode* (e.g. comfort, travel fare), etc.

Ramjerdi (1993) summarizes the possible explanations for these variations. Concerning *trip characteristics*, travel purpose is a source of VTTS variation; travel time savings when commuting to work are usually valued higher than non-work travel time savings. With reference to *socioeconomics*, income may also play a role, mainly because it is associated with the ability to pay or act as a source of taste variation. Furthermore, VTTS is non homogenous across *mode attributes* such as travel time; VTTS may not be linear in time and may vary according to the time components of a trip. Other individual characteristics such as age may also explain some of these variations. Thus, it is a challenging task for the researcher to separate the *sources of variation*; what is practically observed is a multidimensional *joint* distribution of VTTS in the above parameters with non-experimental observations, i.e. the researcher cannot perfectly control the above covariates.

0.2 Problem statement

This study focuses on the *variations of VTTS across transport modes for long distance, private purpose trips in Norway.* The task is to examine why different VTTS estimates are obtained for the various transport modes. More particularly we are examining *mode effects* (e.g. if people adjust their WTP for travel time savings according to the attributes of a mode, because they perceive travelling with a particular mode a unique activity) and *self selection* (e.g. the observed differences stem from the variations in individual characteristics of people, who switch to the transport mode that best fits their WTP) as sources of variation. We also attempt to give an insight into a third effect, namely *strategic behavior*. In *stated preference* (SP) surveys it is highly likely that respondents have an incentive to not reveal their true WTP. This incentive differs across modes, causing respondents to overstate their WTP for some modes and understate it for some others.

Other sources may be exogenous to the consumer choice but *specification* or *estimation-related*, i.e. the VTTS gaps depend on the *employed method of estimation*.

Investigating VTTS differences across modes is quite important in the appraisal of transport investments. Assume that a transport project which is associated with an improvement in the attributes of one or more transport modes is under evaluation. The before-after difference in total benefits depends on:

- *The changes in choice probabilities (changes in market shares)*. Since the *relative levels of attributes will change*, some people will reconsider their choice of transport mode. Therefore, some people will switch to a mode that better suits their profile (user type effects). For example, people with high VTTS may switch to the mode that becomes relatively faster. For example a highway car-only high speed line may induce 'impatient' passengers to switch to car.

- *The change in VTTS for a given mode*. The WTP for time savings in each mode may change, as a result of the attribute modification (mode effects). For example, improved environment in public transport mode may render travelling a more pleasant activity and thus reduce WTP for time savings in that mode.

Knowing the relative impact of the two effects makes it possible to correctly predict the direction of change in total VTTS savings, which is part of the change in total benefits in the context of appraisal schemes. In other words, knowledge over the sources of variation is necessary to predict variation.

0.3 Relevant literature and contribution from this study

A plethora of studies have been dedicated to VTTS, especially in the Western countries. *Value of Time* (VoT) studies have taken place for instance in Norway (Ramjerdi et al., 1997), Sweden (Algers et al., 1998), Denmark (Fosgerau et al., 2007) and Switzerland (König et al., 2003). The latter provides a brief review of the available work in the field.

The Swedish study offers VTTS estimates derived with logit and mixed logit with normal mixing distribution. Fosgerau et al. (2007) is the only work that focuses on the *cross mode variations in VTTS*. Our approach uses a similar methodological basis to the Danish one, namely that it attempts to separate *mode* and *user type effects* by forming user type groups in order to investigate the mode impact within a user type group and the user type impact across user groups in a given mode.

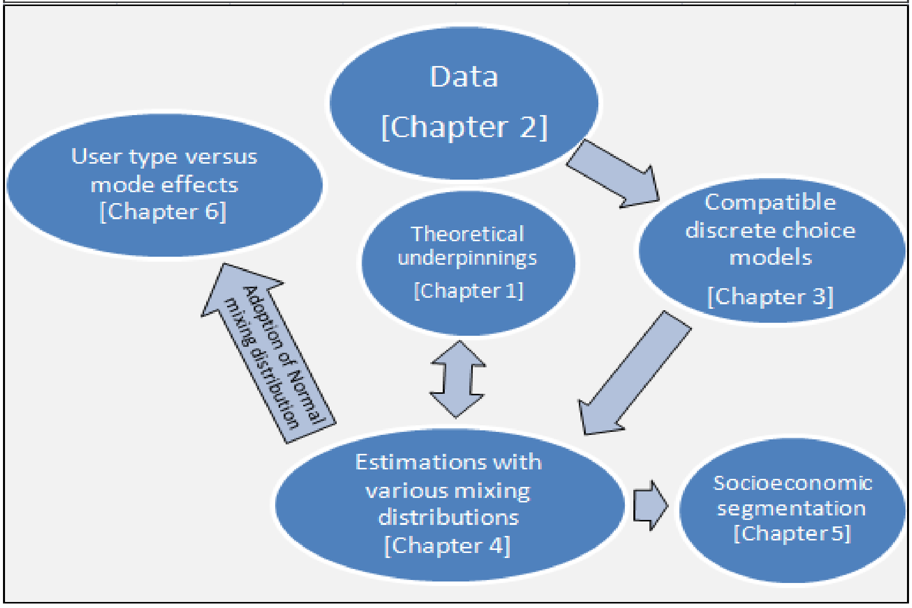
Nevertheless, the methodological basis of the Danish study has been adjusted to fit the Norwegian experimental design and data set. Particularly, VTTS estimates used in the final section are normally distributed in contrast to the Danish study's, in which VTTS is directly parametrized and modeled to follow a lognormal distribution. The exact VTTS formulations of Fosgerau et al. (2007) do not fit the Norwegian experimental design. The experimental design that generated the choice experiments and subsequently the Norwegian SP data set is different than both the Danish and the Swedish corresponding ones (see Chapter 2).

Furthermore, the use of *random coefficient models* (mixed logit) constitutes an adoption of state-of-the-art, recent developments in the field, allowing us to account for *random taste variation*. Since the Norwegian Value of Time study (Ramjerdi et al., 1997) provided only logit estimates, the *re-estimation* with various *mixed logit models* provides an insight into the vulnerability of VTTS estimates to various hybrid models. In that sense, this work extends the result set of the Norwegian VoT study.

0.4 Structure of the thesis

The thesis comprises seven chapters. Chapter 1 discusses the theoretical underpinnings of VoT. The point of departure is the theories of optimal time allocation of Becker and DeSerpa. Some part of the discussion is dedicated on whether discrete choice models are consistent with the economic theory of time allocation. Attention is given to possible limitations that theory suggests on the estimates of econometric models, e.g. negative VTTS. Theory serves mainly as a benchmark and can (if not must) also take feedback from empirical results.

Figure A: Structure and sequence of the thesis



Chapter 2 summarizes the data used in this study. Sections 2.1 and 2.2 discuss the possible advantages of *stated preference* (SP) over *revealed preference* (RP) data in this type of studies. Section 2.3 describes the sampling process and the data set used in the estimations; all estimates in this study refer to long distance trips. Section 2.4 is a brief review of the experimental design employed to generate the *binary choice experiments* used in the survey.

Chapter 3 summarizes the compatible discrete choice methods that can be used in VTTS estimation for *the data set described in Chapter 2*. The described methods are tailor-selected to fit the binary choice experiments. Section 3.1 presents the basic setup of a deterministic discrete choice model, 3.2 focuses on making discrete choice setups operational by *Random Utility theory*. Sections 3.3-3.5 present *binary logit*, *mixed logit* and *binary probit*, the advantages and disadvantages of each. The first two are the models used to estimate VTTS in the empirical part of the study. We highlight the main shortcomings on logit which motivate the use of hybrid models.

Chapters 4 to 6 constitute the empirical part of the study. Section 4.1 provides VTTS estimates from a pure logit model, 4.2 presents a likelihood ratio test for the justification of mixed logit model and 4.3 asserts which coefficients should be random. Estimations with random coefficient models have been carried out with three different mixing distributions. Section 4.4 discusses the behavioral implications for each of them and sections 4.5-4.8 provide estimation results with normal, lognormal and Johnson S_B mixing distribution. A brief conclusion of this chapter is that *estimates are highly sensitive to the assumption of mixing distribution*.

Chapter 5 provides a socio-economic segmentation of VTTS. Section 5.1 investigates the relationship between *income* and VTTS and section 5.2 introduces *gender* in the analysis.

Chapter 6 investigates the effect of three possible sources of variation, namely *user type effects*, *mode effects* and *strategic behavior*. We argue that, *in contrast to* the clear evidence of the Danish study, Norwegian data do not reveal any of these effects to be dominant. It seems however that user *type effects* and *strategic behavior are more evident than mode effects.* Finally, Chapter 7 highlights the most important findings and poses the challenges for future research. A summary of the study's structure is presented in Figure A.

1. Theoretical underpinnings of VTTS

The VTTS is the amount of money (goods) the individual is willing to pay (forego) in order to reduce travel time by one unit. Empirically, VTTS is estimated from discrete choice models as the rate of substitution between time and money in the utility function. '*The interpretation of this ratio depends on the underlying theory that generates such a utility*' (Jara-Diaz, 2000). This chapter provides some review of the theoretical background of VTTS. The various models of time allocation begin from a different (but definitely high) level of abstraction, concerning the heterogeneity of time units and the considered diversity of activities included in the model. As a result, every theory produces different concepts of the value of time, and serves as a different benchmark against the empirical studies of VTTS.

1.1 Becker

Becker (1965) suggested an expanded version of the traditional microeconomic theory of utility maximization which allows for time to enter as a new dimension. The utility function is:

$$U = U(\overline{Z}) = U(Z_1, Z_2, \ldots.., Z_m) \quad (1.1)$$

Z's represent *final commodities* that enter the utility function directly. Every final commodity Z is produced with a combination of *intermediate* goods, **x**, and time in a *household production function*:

$$Z_i = f_i(\overline{x_i}, t_i) \quad (1.2)$$

where vector **t** is m-dimensional. The exact relation between intermediates and time input is not mentioned. Time is considered as an intermediate rather than a commodity itself, i.e. utility cannot be derived from time per se. Each dimension i corresponds to the time spent on the production of a different commodity. Each commodity Z_i, can be produced by a set of intermediate goods and a respective time input. The model *does not* allow for *joint production/consumption activities.*

The optimal allocation of consumption of commodities *Z* implies an indirect allocation of goods and time.

$$U^* = U(x_1^*, x_2^*, .., x_k^*; t_1^*, .., t_n^*) \quad (1.3)$$

Income and time constraints enter the model. Total income, which is the sum of wage and unearned income, has to be spent on market goods:

$$\sum_{i}^{m} p_i x_i = I = V + T_w w_o \quad (1.4)$$

Where w_0 is the average wage, ***p*** is the price vector of the intermediates, and *V* is the unearned income. Total time consists of working time plus time spent on the production of the commodities *Z*. But for every commodity *i* there is the respective time input t_i. Therefore working time equals the total time endowment minus the sum of the time intervals spent on the different dimensions of consumption (i.e. producing commodities). Again, in absence of joint activities:

$$T_w = T - T_c = T - \sum_{i}^{m} T_i \qquad (1.5)$$

Following Jara-Diaz (2000) the Lagrangian for Becker's optimization problem is:

$$\ell = U(Z_1, Z_2, ..., Z_m) - \lambda(V + T_w w_o - \sum_{i}^{m} p_i x_i) - \mu(T - \sum_{i}^{m} T_i - T_w) \quad (1.6)$$

This produces a constant *value of time that is uniform in activities* and equal to the wage rate of the individual. This is supported by the standard economic argument that the marginal utility of time must be equalized for all consumption activities; otherwise, utility can be increased by time reallocation. The same holds between working time and consumption. Therefore in equilibrium, the value of time savings for all activities is equal to zero, while the value of time in consumption activities and work is uniform and equals the wage rate.

If t_i is the unit input of time for Z_i and b_i is the unit input of the market good x_i for Z_i, the production function of commodities can be written as:

$T_i = t_i Z_i \;$ (1.6) and $x_i = b_i Z_i \;$ (1.7)

However, all the constraints can be combined into one equation, what Becker calls '*the full income equation'*. In the special case of *constant average earnings* this is:

$$\sum_{i}^{m} (\pi_i) Z_i = V + T w_o \quad (1.8)$$

A commodity's cost is not only the market price of the goods involved in its production. Its *full price*, denoted by π_i, is the sum of the prices of the goods and of time used per unit of commodity. The sum of all full prices multiplied with the corresponding amounts of commodities *Z* produced is the *full income*: the income that someone would achieve by spending all time available (that means twenty four hours a day, since sleeping is a commodity itself) in working, plus any unearned income. On the left hand side, this income has two components; one part of it is spent directly on market goods ($\sum_i^m (p_i b_i Z_i)$) and one part of it is never realised, but is foregone in leisure activities ($\sum_i^m (t_i w_o) Z_i$).

1.2 DeSerpa

For n goods in consumption, DeSerpa (1971) specifies utility function as:

$$U = U(\overline{X}, \overline{T}) = U(x_1, x_2, .., x_n, t_1, t_2, .., t_n) \qquad (1.9)$$

This formulation differs from Becker's respective, in that utility can be derived from time and goods per se. The *income constraint* is identical to Becker's, all income has to be spent on the n goods:

$$Y = \sum_i^n p_i x_i \qquad (1.10)$$

The *time resource constraint* is:

$$T^o = \sum_i^n T_i \qquad (1.11)$$

The time intervals allocated to the various activities sum up to the initial time endowment. Finally, a set of n inequality *time consumption constraints* imposes *lower bounds* in the amount of time allocated to each of the n goods.

$$T_i \geq a_i x_i \qquad (1.12)$$

The Lagrangian, (1.13), the first order (1.14-1.15) and the complementary slackness conditions (1.16) are:

$$L = U(\overline{x}, \overline{T}) - \lambda(\sum_i^n p_i x_i - Y) - \mu(\sum_i^n T_i - T^o) - \sum_i^n k_i (a_i x_i - T_i) \quad (1.13)$$

$$U_i^{'} = \lambda p_i + k_i a_i, \forall i = 1, 2, .., n \qquad (1.14)$$

$$U_{n+i}^{'} = \mu - k_i, \forall i = 1, 2, .., n \qquad (1.15)$$

$$k_i > 0 \, (= 0 \text{ if } \; a_i x_i < T_i) \qquad (1.16)$$

The adjoint coefficients can be interpreted as marginal increments in utility induced by a marginal relaxation of the corresponding constraint. Thus λ is the *marginal utility of money* *income*; μ is the *marginal utility* of *time as a resource*. The ratio of the two marginal utilities, μ/ λ is the marginal rate of substitution between money and time, a measure often referred to as *the value of time as a resource*.

The *complementary slackness condition* reflects personal, market or institutional constraints in consumption. k_i is the utility increment from a marginal relaxation of the lower bound. If $k_i > 0$ the constraint is binding and the time spent in the specific activity is the minimum time required. In this case, the individual will be better-off if the boundary values decrease. In other words, time savings' values are a matter of *subjective preferences* and *exogenous constraints*.

The idea is that the person is free to deviate from the equality (see 1.16), so that it is a matter of individual preferences if the constraint is binding or not. Since deviation from efficiency is a matter of *subjective preferences*, a leisure good for some may be an intermediate good for others. From (1.15) we can divide by the marginal utility of money and get:

$$\frac{U'_{n+i}}{\lambda} = \frac{\mu}{\lambda} - \frac{k_i}{\lambda} \Leftrightarrow \frac{\mu}{\lambda} = \frac{U'_{n+i}}{\lambda} + \frac{k_i}{\lambda} \qquad (1.17)$$

Since U'_{n+i} is the marginal utility of time allocated to a specific activity *i*, $\frac{U'_{n+i}}{\lambda}$ is the value of time allocated to an activity *i*, or *the value of time as a commodity*. Thus for all intermediate goods, the value of time as a resource is higher than the value of time as a commodity, while for all leisure goods these two measures are equal. The last expression of (1.17), $\frac{k_i}{\lambda}$ is the *value of time savings* in the specific activity *i*.

1.3 Discrete choice models and VTTS

Jara-Diaz (1997) proposes a model for discrete choice, where only one alternative can be chosen from the choice set *M*. Every alternative is associated with a different allocation of time and goods:

$$\max\ U(G, L, W, t_i) \qquad (1.18) \quad \text{s.t.:}$$

$$\text{i) } G + c_i = wW \qquad (1.19),$$

$$\text{ii) } L + W + t_i = T \qquad (1.20),$$

$$\text{iii) } L \geq aG \qquad (1.21)$$

and $i \in M$ .G is the aggregate consumption, L is leisure, t_i and c_i are the travel time and cost associated with the *i*-th alternative, *w* is the wage rate, *W* is the working time and α is the consumption time per unit of *G*. By substituting (1.19) and (1.20) into (1.18) the problem reduces to:

$\max_w \; U[(wW - c_i),(T - W - t_i),W,t]$

s.t $\quad T - W - t_i - a(wW - c_i) \geq 0 \qquad\qquad (1.22)$

From this, the expression for Value of Travel Time is obtained:

$$VTT = \frac{\partial V_i / \partial t_i}{\partial V_i / \partial c_i} = w + \frac{(\partial U / \partial W) - (\partial U / \partial t_i)}{(\partial U / \partial G) - a\theta} \quad (1.23)$$

where V_i is the indirect utility function of i-th choice. Jara-Diaz claims that VTT in (1.23) captures what DeSerpa called '*the value of saving time in a travel activity*'. Despite this Bates (1987), building upon Truong and Hensher (1985) argues that discrete choice models 'capture' the value of transferring time between activities and that the value of time as a resource cannot be separated from the value of time savings in an activity. From (1.23), and by taking into account that $\lambda = (\partial U / \partial G) - a\theta$, one can conclude that *the value of travel time might be higher or lower than the wage rate*, depending on if people prefer one extra time unit in work or as travel time.

It is important to mention that all theoretical models used to derive VTT, involve a high degree of abstraction. Despite incorporating individual preferences and income, they neglect (or cannot incorporate) other socioeconomic variables (age, gender, location) which may affect preferences in the first place and have been proven important factors in empirical settings.

2. Data

2.1 Advantages and Shortcomings of Revealed preference data.

Revealed preference (RP) data is associated with actual choices in real world situations; i.e. the individual reveals its taste or preference through the market choice. This is the main advantage of RP data. If they are collected from a representative sample of the population, they can theoretically replicate the actual market shares.

A second advantage is the *automatic embodiment of both individual and market constraints*. Individual *budget constraints*, for instance, are intrinsic to the observed choice. This is not the case in *stated preference* (SP) data, where the choice is *hypothetical* and *stated;* an individual can state a choice that in reality might not be affordable. Furthermore, market-wide constraints are pre-existent in RP data and impact upon all individuals acting in that market. The *variation in the attributes* is therefore bounded by realistic limitations. For example, the removal of Concorde from plane alternatives means that no person travels from United States to Europe in four hours, not even the wealthy (Hensher, John, & Greene, 2005).

On the other hand, the advantage of *realistically bounded range of attributes* becomes a disadvantage when we aim to predict market changes a priori to new entrants or innovation. *New entrants* means introduction of new alternative products or services which may pose different combinations of attributes than the existing ones. *Innovation* is translated to new, improved attribute levels, or even new alternatives which may have impact upon choice behavior. RP data cannot predict market changes before innovation or new entrance takes place, because the new variation in the attributes has not been previously recorded and new data must be collected to produce models.

Another problem of RP is the *relative absence of attribute variance*. As causes for this, Hensher et al. (2005) name the *market structure*, the *lack of copyright* and *marketing issues*. Concerning the first, microeconomic theory suggests that in a perfectly competitive market products are homogenous, giving rise to zero variance in attributes. 'If data from these markets are used in a choice model, the coefficients of the invariant attributes would be found to be insignificant' (Train, 2002). In RP data, important attributes exhibit the least variation due to the natural forces of market equilibrium. Furthermore, *lack of copyright* and patent protection renders imitation a better strategy than innovation; the levels of the attributes have, therefore, a tendency to converge across alternatives. Finally, marketing issues may suggest that is often easier to change prices than the attributes of the alternatives.

Attribute invariance poses modeling problems to the researcher. Over a population there will exist a distribution of utility for each and every alternative. The purpose of undertaking a choice study is to explain why some individuals reside at one point of the distribution while others reside at other points along the same distribution. An attribute that takes on the same value for all alternatives cannot help explain why individuals reside at the point of the distribution that they do (Bateman et al., 2002). To explain variation in choice we need variation in alternatives.

Another serious shortcoming of RP data is that they fail to provide information on the non-chosen alternatives. The researcher does not really know if the decision maker has experienced them and hence may not be able to use information on the attribute levels of these alternatives or to consider them in the choice set. Furthermore, if the data set consists only of the transactions made, the socioeconomic background of the decision maker is missing. The critical missing data that might explain the choice is never observed.

Finally, a major issue is *collinearity* of the attributes. In many cases, the nature of alternatives is such that their values *move in the same direction*. Contemplate, for example, the choice between two transport modes, bus and taxi. What we observe in RP data is either a choice of bus with low price and comfort and a longer travel time or a choice of taxi with high price and comfort and shorter travel time.

2.2 Stated Preference data

The main shortcomings of RP data are overcome with the use of *Stated Preference* (SP) data. They represent the choices a decision maker claims that would have made under a hypothetical situation, designed by the practitioner. The key element in a stated preference study, like other survey techniques is a properly designed questionnaire (Bateman et al., 2002). The type of questionnaire determines the type of the SP technique employed by the analyst. In general there are two families of methods and therefore data within SP; *contingent valuation* and *choice modeling data*.

Contingent valuation (CV) methods are mainly employed in the valuation of environmental goods, which are not traded in markets. The beauty of a rainforest, for instance, is not a tradable good. Nevertheless, individuals may be willing to pay in order to protect it. The researcher is interested in estimating the distribution of willingness to pay (WTP) over the population. Generally, *CV is preferred when the practitioners try to estimate WTP for the good or service in total and not for its attributes separately. In the later case, Choice Modeling approaches (discussed below) are employed.*

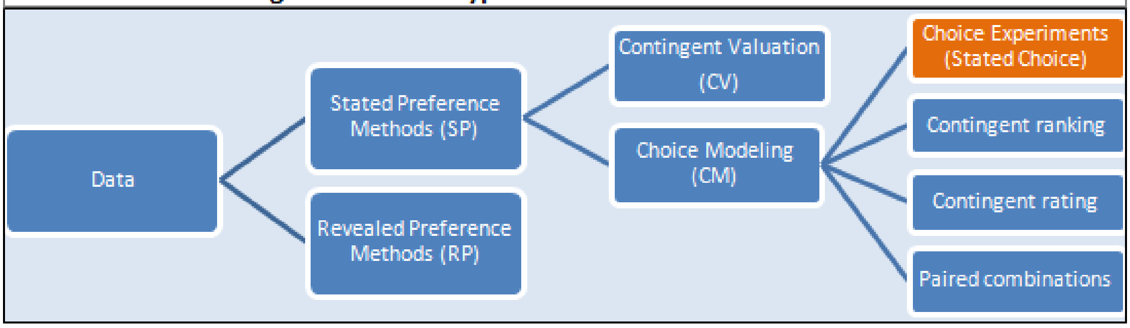
Choice modeling (CM) methods include stated choice methods or *choice experiments* (CE), *contingent ranking*, *contingent rating* and *pair combinations* and, as already mentioned, focus on the WTP for individual attributes of a product or a service.

The data set used in this study contains exclusively observations from *choice experiments*. In choice experiments the respondent faces a sequence of choice sets, each consisting of two or more alternatives. The decision maker chooses *only one* alternative among those in the choice set. We can imagine the choice set as a collection of two or more 'packages'. For example, one choice experiment might consist of two packages. A 20 minutes travel time with 35 NOK fare "package" and a 30 minute travel time with 25 NOK fare. The packages in a choice set are alternatives by construction even if they refer to the same transport mode, as long as attributes vary across them. The analyst is provided with a sequence of choices for every individual, usually 4-9, each from a specific choice set. We briefly discuss the process of setting up choice experiments straight after.

In *contingent ranking* the respondent is asked to *rank the alternatives of a choice set* from the most to the least preferred. This method resembles CE in the sense that it can be seen as a sequence of CEs with shrinking choice set. For example, the individual chooses option F from the choice set A-F; then the choice set shrinks to A-E, a new choice experiment begins and so on.

Contingent rating brings respondents in front of various scenarios, *as alternatives*, and asks them to *rate* the alternatives using a numeric, or semantic scale. Finally, *paired combinations* combine CE elements, in the sense that *the individual states a choice between two alternatives,* and contingent rating elements, in the sense that she has to *rate the strength of the preference using a numeric or semantic scale*. The various methods of data collection are summarized in Figure B.

Figure B: Various types of data collection methods



For the rest, we focus only on the subcategory of *choice experiments*. CE holds many advantages in comparison to both RP and the rest of the SP methods. Their design reduces the extreme collinearity (problem present in RP data). The way that levels of attributes covariate is not as restricted as in the RP case. Returning to the previous example, the choice set can contain a cheap, fast and comfortable alternative and a slow, expensive and less comfortable one. This could not be the case in RP where usually the price, speed and some other attributes, such as better ambience, higher frequency, less stops, vary simultaneously and to a certain direction.

As we argue later on, a full factorial CE design (that is a design in which each attribute level is combined with every level of every attribute to form choice sets) guarantees *orthogonality.* The latter is important in order to form and investigate trade-offs between attributes, like the *Value of Travel Time*. In case of strong collinearity, it is impossible to say what the trade-offs are, i.e. relative effects cannot be derived, since variables move together.

Second, an alternative in a CE set may be a package of attribute values that go beyond the existing technological frontier. This is useful in transport research in order to analyze new modes, infrastructure and service levels that do not currently exist. Travel time can be very short, fares may vary outside the current ranges and new hypothetical facilities may enter as attributes. Innovation and entrance can be facilitated by the CE method which may be used to predict market changes in case of new product penetration or service improvement. Hence, CE can accommodate preference changes when the *attributes levels go beyond the technological frontier*.

As pointed earlier, variation in attribute levels is necessary to understand why variation in choice exists. Attribute variance is accommodated in CE; a hypothetical situation can deviate from a reality that may be characterized by attribute invariance.

CE is also superior to CV when it comes to “yes-saying”, a type of socially correct bias. In CV, the analyst asks directly for the individual’s WTP and it is very probable that the individual will not reveal the actual WTP. This can happen either because saying yes is a socially correct answer (“socially correct” bias) or because the person has an incentive to hide its real WTP by overstating or understating it (strategic behavior).

The main disadvantages of CE in comparison with conventional RP coincide with the advantages of RP discussed in the previous section. That is, the advantages of RP mirror the disadvantages of CE and vice versa.

Sections 2.1 and 2.2 provided arguments in favor of CE. The forthcoming sections describe the actual sampling process and the design of the *choice experiments* in this study.

2.3 Sampling and data set.

This study uses data on long distance travel from the data set collected in the Norwegian Value of Time (VoT) study (Ramjerdi et al., 1997). The long distance modes of transport covered in the Norwegian VoT study are: car, plane, ferry, bus and train. The ferry subpopulation is excluded from our work. Also, all observations with business travel purpose are excluded.

The sampling approach was *choice based*, i.e. the respondents were recruited connected to their choice of transport mode. The data collection has been carried out in two waves. The first wave was conducted in March-April 1995 and the second took place in September-October 1995. The data set contains 1511 interviews from the first and 1538 interviews from the second wave. Four pilot studies were conducted in addition to the main study. The total number of interviews from these studies is 378.

Figure C summarizes the recruitment and interview locations and the actual number of interviews by mode. The recruitment of car drivers was carried out by phone. The target group was those who had made a long distance trip in the previous two weeks. The sampling was forced to recruit equal number of respondents whose *reference trip* was 30-100 km, 101-300km and over 300km; every group contains 300 interviews. In other words, the car sub-sample is *stratified*.

Figure C: Interviews. Recruitment, place of interview and number of interviews by mode.

MODE	CAR	PLANE	BUS	TRAIN
RECRUITMENT	PHONE	AIRPORT/ ON BOARD	ON BOARD	ON BOARD
INTERVIEW	HOME	HOME/ ON BOARD	ON BOARD	ON BOARD
NUMBER OF INTERVIEWS	900	500	500	900

Plane passengers were recruited at the airport or on board, depending on the permission from the operator to recruit people during a flight and to conduct interviews. Those who were recruited on board were also interviewed on board. Those recruited at the airport were interviewed at home. Concerning bus passengers, the range of travel time of the trips in which respondents were recruited is 2.5-10 hours. The corresponding range for rail passengers is 1.5-9 hours. All recruitments and interviews for bus and train took place on board. Computer assisted personal interviewing technique (CAPI) was used in the study.

During recruitment for the mode car, the respondent was asked to describe a long distance trip he/she *had made the last two weeks*. This is the *reference trip*; it contains the *actual choice* of mode, the *reference mode*, and the *characteristics of the trip* (distance, purpose, perceived travel time, travel cost, etc.). The reference trip for the scheduled modes was the intercepted trip. The respondent was also asked to provide his/her socioeconomic data (income, family status, working status, age, etc.).

2.4 Design of choice experiments

Based on the *reference trip* and *reference mode*, a respondent was given a sequence of 11 *binary choice experiments* (one SP game). Every binary choice was *within-mode*, i.e. a choice between a pair of alternative attribute combinations of the *reference mode*. Only three attributes were used in all choice experiments. Figure D summarizes the attributes used for each mode.

Figure D: Attributes used for each mode and study

MODE(STUDY)	ATTRIBUTE 1	ATTRIBUTE 2	ATTRIBUTE 3
CAR	COST	IN VEHICLE TIME	AUTOMATIC TRAFFIC CONTROL
PLANE (WAVE 1)	PRICE	ON BOARD TIME	FREQUENCY
PLANE (WAVE 2)	PRICE	AIRPORT –AIRPORT TIME	FREQUENCY
BUS	PRICE	IN VEHICLE TIME	FREQUENCY
TRAIN	PRICE	ON BOARD TIME	FREQUENCY

Using the values of the attributes in the reference trip as *base values*, four levels for cost and travel time and three for frequency of services (scheduled modes) and automatic traffic control (car) were generated as percentages of the base values. Figures E and F show the percentage changes of the attributes relative to the base values for car and scheduled modes respectively.

Figure E: Attribute levels in the choice experiments for CAR

ATTRIBUTE	LEVEL 1	LEVEL 2	LEVEL 3	LEVEL 4
PRICE	-X%	BASE VALUE	+0.4X%	+X%
IN VEHICLE TIME	-25%	-10%	BASE VALUE	25%
AUTOMATIC TRAFFIC CONTROL	PRESENCE OF SPEED DETECTOR	MORE SPEED DETECTORS IN 50-60KM/H ZONES	MORE SPEED DETECTORS IN ALL ZONES	

Figure F: Attribute levels used in the choice experiments for the scheduled modes

ATTRIBUTE	LEVEL 1	LEVEL 2	LEVEL 3	LEVEL 4
PRICE	-X%	BASE VALUE	+0.4X%	+X%
TRAVEL TIME	-25%	-10%	BASE VALUE	25%
FREQUENCY	-50%	BASE VALUE	50%	

The design of the experiment was based on a *pre-assumed range of VoT*. The VoT range, along with the percentage change in travel time determines the value of the X, which is the percentage change in cost. The design used is *randomized fractional factorial*, i.e. the choice sets do not include all possible combinations of a full factorial. Dominant choice pairs were not included in the experiment.

Apart from the *reference mode* a respondent was asked to choose an *alternative transport mode* for the exact *same trip.* A second SP game with 11 choice experiments was then given to the respondent. In summary, each interview generated two SP data sets. The first contains the answers for the choice experiments for the *reference mode* and the second the responses for the *alternative mode*. We return to the use of these data sets later on, in the empirical part.

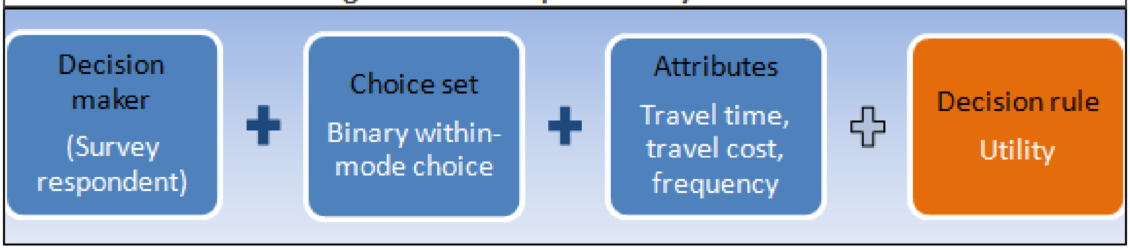
3. Discrete choice and Random Utility models.

3.1. Framework set up for a deterministic choice theory

'A specific theory of choice is a collection of procedures that defines the following elements' (Ben-Akiva & Lerman, 1985: pp.32): i) decision maker, ii) choice set, iii) attributes of the alternatives and iv) a *decision rule*. Elements *i* to *iii* have been determined through the stages of experimental design; the respondent is exposed to a binary choice situation between two different combinations of the attributes travel time, travel cost, and a third attributed (frequency or automatic traffic control) *for the same mode*. Nevertheless, without a decision rule this framework set up is incomplete, since it does not describe the internal mechanism used by the decision maker to analyze information and end up in a unique choice.

The instrument used as decision rule in this study is *utility*. The accompanying assumption is that the respondent is attempting to maximize utility through the choice. Thus, in a choice set with alternatives L and R, the choice of L yields $U_L > U_R$ and vice versa. The following figure summarizes framework set up for a deterministic discrete choice theory.

Figure G: The setup of a theory of choice



3.2. Random Utility Models

A deterministic framework implies that identical choice situations result in identical decisions across i) time and ii) individuals. However, in choice experiments, decisions have been observed to be inconsistent with respect to both of them. This gave rise to the development of *Random Utility Models* (RUM), which is the toolkit that economists use to study discrete choice.

The generation of RUM is based on a double assumption. First, preferences remain *deterministic from the decision maker's point of view*, such that *if the experiment is replicated for the same person the decision outcome will be identical* (Dagsvik, 2000). Thus, RUM retains a deterministic profile across choice situations, in contrast to other behavioral models (proposed by psychologists) which allow for an individual's utility (preferences) to vary according to their 'psychological state', such as the Thurstone model.

Second, preferences become *random from the econometrician's point of view*, in the sense that observational deficiencies render the exact form of utility unknown to the analyst. Consequently, RUM 'admits' that *if the experiment is replicated for different individuals the decision outcome does not have to be identical*. Therefore, RUM introduces a probabilistic profile across decision makers. The probability that decision maker *n*, chooses alternative *j* in a binary choice situation between L and R is:

$$\Pr(j \mid L, R) = \Pr(U_{nj} > U_{ni}), i, j = L, R. i \neq j \tag{3.1}$$

We assume that the *random utility* has an additively separable structure:

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{3.2}$$

The first part is a deterministic term which is specified as a function of the observable attributes and individual characteristics. It is often called the *systematic utility*. The second term is a random variable with a hypothetical distribution. It is the part of utility that the researcher does not observe. See Dagsvik (2000) for a summary of the 'sources of uncertainty that give rise to randomness in preferences'. Substituting (3.2) into (3.1) yields:

$$\Pr(U_{nj} > U_{ni}) = \Pr(V_{nj} + \varepsilon_{nj} > V_{ni} + \varepsilon_{ni}) = \Pr(\varepsilon_{ni} - \varepsilon_{nj} < V_{nj} - V_{ni}) \tag{3.3}$$

Two assumptions remain for the model to become operational. The first is the specification of the systematic part of utility. Various specifications are examined throughout the empirical part of this study. The second assumption concerns the structure of the error terms. It turns that different assumptions about the error difference lead to different Random Utility Models. From (3.3) we have:

$$\Pr(\tilde{\varepsilon}_n < V_{nj} - V_{ni}) = \int_{-\infty}^{V_{nj} - V_{ni}} f(\tilde{\varepsilon}_n) d\tilde{\varepsilon}_n = F(V_{nj} - V_{ni}) \tag{3.4}$$

Thus, any cumulative distribution function can give rise to RUM.

3.3. Binary logit

If we assume that ε is *identically and independently distributed extreme value type I* (*iid EV1*) across the two alternatives (L,R) and decision makers, it can be shown that the error difference is logistically distributed with cumulative distribution function:

$$F(\tilde{\varepsilon}_n) = \frac{1}{1+\exp(-\mu\tilde{\varepsilon}_n)} \quad \mu > 0,\ -\infty < \tilde{\varepsilon}_n < \infty \tag{3.5}$$

where μ is the scale parameter of the distribution. In order for choice probabilities to be identifiable, μ has to be fixed to an arbitrary value. A popular choice is μ=1. By combining (3.4) and (3.5) we get the choice probabilities for the two alternatives:

- $\Pr(L \mid L,R) = \dfrac{\exp(V_{nL})}{\exp(V_{nL})+\exp(V_{nR})}$ and
- $\Pr(R \mid L,R) = \dfrac{\exp(V_{nR})}{\exp(V_{nL})+\exp(V_{nR})}$ (3.6)

If we further assume linear-in-parameter systematic utilities:

$V_{nL} = \beta' x_{nL}$ and $V_{nR} = \beta' x_{nR}$

the choice probabilities can be written as functions of the parameters. Then (3.6) becomes:

$$\Pr(L \mid L,R) = \frac{\exp(\beta' x_{nL})}{\exp(\beta' x_{nL})+\exp(\beta' x_{nR})} \text{ and } \Pr(R \mid L,R) = \frac{\exp(\beta' x_{nR})}{\exp(\beta' x_{nL})+\exp(\beta' x_{nR})} \tag{3.7}$$

The power of logit as a model lies in its *convenient properties*. From (3.6) we can check that the choice probabilities are attained in a *closed form expression* and *sum up to one*. It must be highlighted that this is not the case in models that are reviewed later, such as the *probit* and *mixed logit* since there is no closed form expression for their choice probabilities. This is intuitively correct and extends directly to choice sets with *J* alternatives, where Multinomial Logit (MNL) choice probabilities add up to:

$$\sum_{i=1}^{J} P_{ni} = \sum_{i=1}^{J} \left[\frac{\exp[V_{ni}]}{\sum_{j} \exp[V_{nj}]}\right] = 1 \tag{3.8}$$

Second, and in contrast to the linear probability model (Maddala, 1983: p.16) from (3.6) it can be confirmed that the logit choice probabilities, necessarily belong to the interval [0,1]. Third, 'the *relation of the logit choice probability to the representative utility is sigmoid*. If the representative utility of an alternative is very low compared to the corresponding of other alternatives, a small increase in the utility of the alternative has little effect on the choice probability' (Train, 2002). This has clear policy implications; the logit model suggests that improvements in the attributes of an alternative (increase in its representative utility) have greater effect when the binary choice is ambiguous, that is when the choice probability is close to 0.5.

The *limitations* of logit are summarized in three areas: i) random taste variation ii) panel data and iii) substitution patterns.

i) Logit can capture *taste variation* but only within certain limits. Tastes that vary systematically with respect to observed variables can be incorporated in logit models, *unlike tastes which are correlated with unobserved variables or vary purely randomly*. Suppose that differences in taste are reflected in the coefficients of the attributes of the transport modes, which we now allow to be individual specific. The impact of a given attribute in the *n*-th individual for a given alternative *j* varies over individuals, so utility is specified as:

$$U_{nj} = \alpha + \beta_T^n TT_j + \beta_C C_j + \varepsilon_{nj} \qquad (3.9)$$

The systematic utility of a transport alternative is assumed to be a linear function of travel time (TT) and travel cost (C). We now allow the time coefficient to vary with respect to income of the individual plus some other factors (frequency of travelling, distance, number of children at home etc) that are not observed and hence are modeled as random:

$$\beta_T^n = \vartheta I_n + \eta_n \qquad (3.10)$$

Substituting (3.10) in (3.9) yields:

$$U_{nj} = \alpha + [\vartheta I_n + \eta_n]TT_j + \beta_C C_j + \varepsilon_{nj} = \alpha + \vartheta I_n TT_j + \beta_C C_j + [\eta_n TT_j + \varepsilon_{nj}] \qquad (3.11)$$

The new composite error is not *iid extreme value type I*. The covariance of the term for two alternatives *i,j* is:

$$Cov(\widetilde{\varepsilon_{nj}}, \widetilde{\varepsilon_{ni}}) = Cov(\eta_n TT_j + \varepsilon_{nj}, \eta_n TT_i + \varepsilon_{ni}) = Cov(\eta_n TT_j, \eta_n TT_i) = (TT_j TT_i) Var(\eta_n) \neq 0 \quad (3.12)$$

and is not zero if the error term η has positive variance. Furthermore, the variance of the error term is different across alternatives, violating assumption of *identically distributed error terms*. By the assumption that μ=1 the variance of the composite term:

$$Var(\widetilde{\varepsilon_{nj}}) = Var(\eta_n TT_j + \varepsilon_{nj}) = TT_j^2 Var(\eta_n) + \frac{\pi^2}{6} \qquad (3.13)$$

depends on the chosen alternative. Logit is therefore a misspecification in the case of random taste variation. Despite this, the researcher may still choose to use the logit for the sake of simplicity. But neither does a guarantee exist that logit model approximates the average tastes nor does it provide information on the distribution of tastes around the average. The alternative option is to use a *probit* or a *mixed logit* model, which can -as we argue in the forthcoming sections- fully incorporate random taste variation.

ii) The second significant limitation of logit is related to the use of *panel data*. These are repeated observations of multiple entities or individuals over time. As in the previous case, logit remains a good model as long as the error terms are *iid*. *Dynamics in the observed factors* (attributes of the alternative or socioeconomic variables) can be accommodated; the inclusion of lags does not induce inconsistency in the estimation. On the other hand, *dynamics associated with unobserved factors cannot be handled*, since they can carry across individuals and alternatives.

The inefficiency of logit becomes apparent in this study, which uses a *SP data set*. This involves multiple binary choices from the same individual. Consider again *travel time* (TT) and *travel cost* (C) as attributes of the alternative. The utility from alternative *j* is:

$$U_{njt} = \alpha + \beta_T TT_{jt} + \beta_C C_{jt} + \varepsilon_{njt} \qquad (3.14)$$

where the subscript *t* denotes the number of the choice experiment for an arbitrary respondent. Suppose that the error term contains unobserved socioeconomic variables which do not vary over choice experiments or alternatives:

$$\varepsilon_{njt} = \gamma + \overline{\delta \overline{w}^{n}} + \eta_n \qquad (3.15)$$

where $\boldsymbol{\delta}$ is a vector of coefficients, $\boldsymbol{w}$ a vector of socioeconomic variables that are fixed across *J* alternatives and *T* choice experiments for a given respondent *n* and η is iid in *n, j* and *t*. From (3.15) it can be confirmed that ε is not *iid* across choice experiments. Thus, *logit is a misspecification in SP multiple choice experiments unless every omitted factor that remains fixed across choices is fully incorporated in the systematic part of utility*. Train (2002) recommends using a more flexible model such as probit or mixed logit or trying to include the unobserved factors into representative utility so that the remaining errors are iid over experiments.

iii) The *substitution patterns* of logit and specifically the *Independence of Irrelevant Alternatives* (*IIA*) property is the most widely discussed limitation in bibliography. A model is said to exhibit IIA when the relative odds of choosing alternative *j* over *i* do not depend on what other alternatives are available or what the attributes of the other alternatives are.

This might not make sense at first, since the data used in the study relate to *binary choice sets*, but it is worth having a brief look at this property. The choice probability ratio for binary logit is:

$$\frac{P_{nit}}{P_{njt}} = \frac{\exp[V_{nit}] / \exp[V_{nit}] + \exp[V_{njt}]}{\exp[V_{njt}] / \exp[V_{nit}] + \exp[V_{njt}]} = \frac{\exp[V_{nit}]}{\exp[V_{njt}]} \tag{3.16}$$

Adding a third alternative in the choice experiments leaves the odds unaffected.

IIA is the direct outcome of the fundamental assumption upon which logit builds, namely that the error terms are *iid* (the covariance matrix of the error terms is a diagonal matrix). McFadden (1974) proves that logit choice probabilities are obtained exclusively from *iid type EV1* errors, even across alternatives. IIA is a rather strong assumption, since the binary choice experiments of this study are *within-mode*, i.e. the *two alternatives* are actually different levels of attributes (travel time, cost, comfort etc.) for the *same transport mode.* Thus, there is an extra argument against the *iid* assumption, namely that the unobserved factors that influence choice may correlate stronger between two alternative attribute combinations of the same transport mode that between two different alternative modes.

3.4. Mixed logit

Mixed logit models can be specified as both *random parameter models* and *error component* models. As it is shown below, the estimation outcome is essentially the same. In the *random* parameter specification, we assume once again that the individual *n* is faced with a choice among J alternatives (binary choice in this study) in T choice situations. The linear in parameters utility for choosing alternative j in the choice experiment t is:

$$U_{njt} = \beta_n^{'} x_{njt} + \varepsilon_{njt} \tag{3.17}$$

where $\boldsymbol{x}$ is a vector of attributes of the alternative or socioeconomic characteristics and ε and β_n are unobserved influences which are treated as stochastic. As in the pure logit model, the error term ε is assumed to be *iid EV1* distributed. The parameter coefficients, however, are random across individuals accounting for random taste variation. We can decompose these coefficients into their mean *b* and deviations η_n, or $\beta_n = b + \eta_n$. If we substitute back to (3.17) we get:

$$U_{njt} = b' x_{njt} + [\eta_{njt} + \varepsilon_{njt}] \tag{3.18}$$

where ε is *iid EV1* but η can practically be assumed to follow any distribution. The expression in (3.18) represents an *error component model*; in this approach the standard deviation of the random parameter 'stores' the heterogeneity as a separate error component. The estimation outcomes of the two models are identical (Hensher & Greene, 2001).

The conditional choice probabilities are logit. This is if η_n was known with certainty for an individual then the remaining of the error term in (3.18) would be *iid EV1 distributed*. The conditional on β choice probability for a sequence of T choices, one for each choice experiment t is a product of logit formulas:

$$P_{njt}(\beta) = \prod_t^T [\frac{\exp(\beta_n' x_{njt})}{\sum_j^J \exp(\beta_n' x_{njt})}] \tag{3.19}$$

The unconditional probability is the above probability weighted over all values of β:

$$P_{njt} = \int_\beta \prod_t^T [\frac{\exp(\beta_n' x_{njt})}{\sum_j^J \exp(\beta_n' x_{njt})}] f(\beta \mid \Omega) d\beta \tag{3.20}$$

Mixed logit choice probabilities are a mixture of a logit choice probability with a *mixing distribution* f. "The probabilities do not exhibit IIA and different substitution patterns are obtained by the appropriate specification of the *mixing distribution*" (Hensher and Greene, 2001). The probability in (3.20) cannot be calculated in closed form, but can be approximated by *simulation*. Mixed logit models are often referred to as *hybrid models* for this reason; one part of the resulting choice probability has a closed form and the rest requires simulation.

Frankly speaking, *simulation* is a sort of imitation of some process. A *simulated choice probability* is generated to 'mimic' the real choice probability in the following way. A value of β is drawn from the mixing distribution with parameter vector **θ**, f(β|θ). For this arbitrary value, the conditional choice probability is calculated. This process is repeated many times; the number of necessary draws depends on how fast the simulated choice probability converges to the actual one, which in turn depends on the variance of the mixing distribution assumed. The simulated probability is the weighted average of the R conditional probabilities produced by R draws.

$$\widetilde{P_{njt}} = \frac{1}{R} \sum_{r=1}^{R} L_{njt}(\beta^r) \tag{3.21}$$

The parameters of the mixing distribution are then estimated by *maximum simulated likelihood estimation.* The *simulated log-likelihood function* is:

$$SLL(\theta) = \sum_{n=1}^{N} \sum_{j=1}^{J} d_{nj} \ln \widetilde{P_{nj}} \tag{3.22}$$

where d_{nj} equals one when individual *n* chooses *j* or zero otherwise, and *N* is the number of individuals. Hence, for each individual, R draws are generated and the simulated probabilities for all alternatives are calculated.

When it comes to using mixed logit, a plethora of specification issues arise which constitute the main challenges in its application. The first is to select which of the parameter coefficients will be random and which are going to be kept fixed. A second one to decide in favor or against recommended mixing distributions. The choice of the mixing distribution is a central issue. 'Actually, various pieces of research have demonstrated that an inappropriate choice of the distribution may lead to serious bias in model forecast and in the estimated mean of random parameters' (Fosgerau & Bierlaire, 2007). Panel data, often in the form of stated choices also pose a challenge since the researcher has to somehow account for the fact that several choices come from the same individual. These problems will be further discussed from an empirical point of view as we proceed to the specification of our econometric model.

3.5. Binary probit

'One logical assumption is to view the disturbances as the sum of a large number of unobserved but independent components. 'By *central limit theorem* the distribution of disturbances would tend to be normal'(Ben-Akiva & Lerman, 1985). The *binary probit* model is derived from the assumption that the disturbances of the two alternatives (L,R) are both normal with zero mean, variances σ_L^2, σ_R^2 and covariance σ_{LR}. The distribution of the error difference is

$$\tilde{\varepsilon} \sim N(0, \sigma_L^2 + \sigma_R^2 - 2\sigma_{LR}) \tag{3.23}$$

is also normal. Then (3.4) becomes:

$$\Pr(\tilde{\varepsilon}_n < V_{nj} - V_{ni}) = \int_{-\infty}^{V_{nj}-V_{ni}} \frac{1}{\sigma\sqrt{2\pi}} \exp[-\frac{1}{2}(\tilde{\varepsilon}/\sigma)] d\tilde{\varepsilon}_n = \Phi(\frac{V_{nj} - V_{ni}}{\sigma}) \tag{3.24}$$

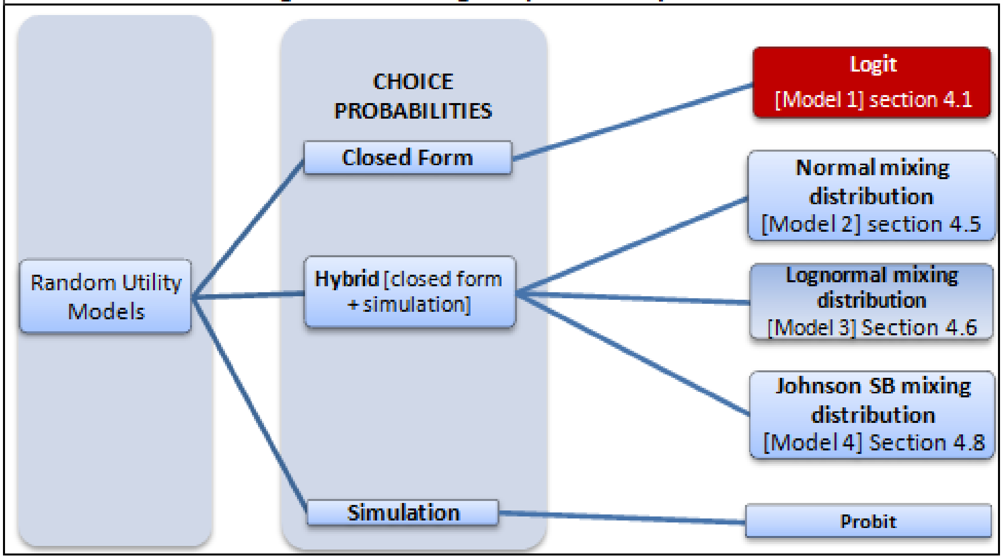
where 1/σ is the scale of utility. By allowing error terms to follow any pattern of correlation, probit can accommodate the main drawbacks of logit. It can be shown that probit choice probabilities do not exhibit the *IIA* property (since disturbances can follow any pattern of correlation). Probit can also handle random taste variation, as long as any random coefficient follows a normal distribution with mean *b* and standard deviation *σ*.

Despite these desirable properties, the choice probability does not have a closed form expression and can only be approximated by simulation. This fact rendered probit models less attractive than mixed logit, in which only one part of the choice probability has to be approximated by simulation. Probit models will *not* be used in this study.

4. VTTS estimations

4.1. Estimation of VTTS with Logit specification

Figure H: Pure logit as point of departure



We set as point of departure the simplest form of MNL model in which the utility of the chosen alternative is a linear function of the required travel time, cost and F. F, the third attribute, is frequency for the scheduled modes and 'automatic traffic control' for car. The respondent faces a sequence of *within-mode* binary choice situations between two alternatives (both alternatives refer to the same transport mode, i.e. the reference mode, they are considered as different alternatives, however, since the levels of attributes are different). In each choice situation, we denote them as left (L) and right (R). The choice of L and R is arbitrary. For instance numbers (1 and 2) could have been used instead. We specify the *systematic utility* as linear in the attributes travel time (TT), cost (C) and frequency (or automatic traffic control) (F).

$$V_L = \alpha + \beta_{time}TT_L + \beta_{\cos t}C_L + \beta_{freq}F_L$$

$$V_R = \quad \beta_{time}TT_R + \beta_{\cos t}C_R + \beta_{freq}F_R \qquad \textbf{(Model 1)} \qquad (4.1)$$

The coefficients of the attributes are specified to be *generic*, i.e. not alternative specific, since they all refer to the same transport mode. We also introduce an *alternative specific constant* for the left alternative. This constant is interpreted as the average effect of the omitted factors on the utility of the left alternative *relative* to the right (Train, 2002). Since both L and R refer to the same transport mode, this term is not expected be significantly different than zero. It should be included, however, to check for *order effects* and *lexicographic answers*. Significance of this term would be a sign that some of the respondents answered lexicographically, or that there is something intrinsic in the design of the questionnaire that favors one of the alternatives.

Despite this, the structure of the randomized fractional factorial does not suggest any reason that could make an alternative more favorable just because it appears on the left or right side of the screen. The same structure also rules out *lexicographic answers*, i.e. answers that reflect decisions taken with respect to one attribute (for example, the respondent always chooses the cheapest alternative), to be the reason for favoring an alternative because of the order of appearance on the screen. It is however possible that some respondents systematically choose an alternative because of the order of their appearance on the screen. Since with roman alphabets people read from left to right, it is likely that some respondents would select the first alternative they see on the screen, the left one.

We estimate the parameters of Model 1 with BIOGEME 1.5 (Bierlaire, 2003) for the four strata; car drivers and plane, bus and train passengers (one sub-model for each group). Both coefficients are specified to be constant in the population. Therefore we get a constant estimate of value of travel time (VTT) for each stratum. The estimation results are presented in Table 1. The estimates of VTT from every sub-model are expressed in 1995 Norwegian Kroner (NOK) per minute of travel time. Therefore, they must be multiplied by 60 to give an estimate of per hour VTT. The estimates of per hour VTT are approximately: 88 NOK/hour for car, 179 NOK/hour for plane, 35 NOK/hour for bus and 48 NOK/hour for train.

Table 1: BIOGEME estimates for Model 1 (sub-models 1a-1d)

MODE	**CAR** (submodel 1a)	**PLANE**(submodel 1b)	**BUS** (submodel 1c)	**TRAIN** (submodel 1d)
B_time	-0.0208	-0.0311	-0.00452	-0.0086
Robust Std Err.	0.00181	0.00436	-0.00105	0.000781
Robust t-test	-11.46	-7.12	-4.3	-11
p-value	0	0	0	0
B_cost	-0.0141	-0.0104	-0.00767	-0.0108
Robust Std Err.	0.0012	0.00191	0.00105	0.000799
Robust t-test	-11.7	-5.46	-7.32	-13.46
p-value	0	0	0	0
VTT	1.474	2.97585	0.589535	0.798708
Robust Std Err.	0.08806	0.3561	0.1014	0.0668
Robust t-test	16.75	8.398	5.811	11.91
p-value	0	0	0	0
B_F (frequency or ATT)	-0.128	-0.00295	0.000206	0.000148
Robust Std Err.	0.0236	0.000711	0.00013	0.000372
Robust t-test	-5.43	-4.15	1.59	0.4
p-value	0	0	0.11	0.69
Constant	0.00331	-0.00238	0.0825	0.0263
Robust Std Err.	0.0286	0.0498	0.0349	0.0282
Robust t-test	0.12	-0.05	2.37	0.93
p-value	0.91	0.96	0.02	0.35
Nr. of observations	6594	2313	3960	6088

The estimates of β_{time} and β_{cost} are significantly different than zero in all sub-models. The *robust t-tests* are relatively high to guarantee zero p-values. Thus, the null hypothesis of insignificant time or cost coefficients is rejected at every convenient level of significance. The robust standard error and consequently the t-test for the VTTS have been computed from a second-order Taylor series approximation. Again, the high t-values in the four sub-models imply that the hypothesis of insignificant VTT can be rejected at any level of significance.

The flexible third attribute is not significant in all sub-models. In the car sub-model, it refers to the number of photo-box speed detectors in a given stretch of the road (see Chapter 2). The estimate is statistically significant and negative, implying that drivers perceive speed detectors as a hurdle on the desired speed or perhaps a worry about exceeding the speed limit and getting a fine. For the rest of the modes, the attribute refers to frequency and is associated with the time interval between two departures. The estimate for plane passengers is negative and highly significant –the longer the time intervals between flight departures the lower is the utility with plane. The frequency coefficient estimates for bus and the train sub-models are insignificant.

The insignificance of the *alternative specific constant* in car, plane and train sub-models is not surprising; the omitted factors that generate (dis)utility are identical for the alternatives L and R, since the two alternatives refer to the same transport mode. Thus the average impact of omitted factors should not be different for the two choices. In the bus case, however, the null hypothesis for insignificant within mode constant is rejected at levels of significance smaller than 0.02, as the p-value suggests. In this case, p-value is the probability of estimating a bus constant at least as different than zero as 0.0825, assuming that this constant is in fact zero (Stock & Watson, 2003: pg. 113).

A re-estimation of the sub model for bus without constant sheds light in the paradox; the coefficient estimates, and consequently the estimate VTT, are almost identical. Table 2 presents these results.

Table 2: BIOGEME estimates for submodel 1c without constant

BUS (submodel 1c)	B_time	B_cost	VTT	B_frequency
Coefficient	-0.00451	-0.00765	0.5897	0.000202
Robust Std. Err.	0.00105	0.00105	0.1022	0.00013
Robust t-test	-4.3	-7.31	5.771	1.56

We now turn to the discussion of the summary statistics that accompany the estimation process and are placed in table 3.

Table 3: BIOGEME summary statistics for Model 1

MODE	Null LogLik	Initial LogLik	Final LogLik	LogLik Ratio Test	ρ^2	adj.ρ^2	final gradient norm
CAR	-4570.613	-4570.613	-3909.986	1323.053	0.145	0.144	0.02462
PLANE	-1603.249	-1603.249	-1414.685	377.13	0.118	0.115	0.009879
BUS	-2744.863	-2744.863	-2579.592	330.541	0.06	0.059	0.02274
TRAIN	-4219.88	-4219.88	-3751.855	936.051	0.111	0.11	0.0164

For each of the sub-models, the *null log-likelihood*, $L(0)$, is the value that the log-likelihood function attains when all parameters are set to zero. "In binary choice models it is the log likelihood of the most 'naive' model, that is, one in which the choice probabilities are ½ for each of the two alternatives" (Ben-Akiva & Lerman, 1985). The *initial log-likelihood*, $\mathrm{L}(\overline{\beta}_0)$, shows the value of the log likelihood function before any maximization algorithm is applied. It depends on the initial assigned parameter values by the researcher. We fixed initial values of betas to zero. The *final log-likelihood*, $L(\widehat{\beta}_{mle})$, is the value that the log likelihood attains when its vector of parameters is replaced by the ML vector of estimates, $\widehat{\beta}_{mle}$.

The *log-likelihood ratio test* (LR test) is used the same way F-test is used in linear regression models, i.e. to test for the hypothesis that the 'real' model is significantly different than the 'naïve', in which all parameters equal zero. The associated test statistic has unknown small-sample distribution, but is distributed asymptotically as a chi-square (χ^2) with degrees of freedom equal to the number of restrictions being tested (Kennedy, 2003). Knowing that the null distribution is χ^2 makes possible for the construction of rejection region for any level of significance. In the present case the test rejects the null hypothesis if:

$$\text{LR-test} = -2[L(0) - L(\widehat{\beta}_{mle})] > \chi_4^2(\alpha) \qquad (4.2)$$

since four parameters are restricted to be zero under the null hypothesis. The LR tests of all sub-models are high enough to reject the null hypothesis at any level of significance. Ben-Akiva and Lerman (1985:pg165) argue that LR test is not very useful since it almost always rejects the null hypothesis, even at a very low level of significance.

The ρ^2 and the adjusted-ρ^2, or *McFadden's likelihood ratio index*, are informal indexes for the goodness of fit which are analogous to R^2 and the adjusted-R^2 in linear regression and -in a nutshell- measure how much of the initial log-likelihood is explained by the model (Ben-Akiva and Lerman, 1985). The formulas for the two indexes are:

$$\rho^2 = 1 - [\frac{L(\widehat{\beta}_{mle})}{L(0)}] \qquad (4.3)$$ and

$$\text{adjusted-}\rho^2 = 1 - [\frac{L(\widehat{\beta}_{mle}) - K}{L(0)}]. \qquad (4.4)$$

The very high values of the final likelihood relative to the number of parameters K=4 explain why the differences between these indexes are tiny. The adjusted likelihood ratio is between 0.11 and 0.144 for all transport modes apart from bus, for which ρ^2 is much lower, 0.06. Greene (2003) points out that this measure has an intuitive appeal in the sense that it is bounded between zero and one and that it increases as the fit of the model improves but -unlike R^2 in linear regression- its values have no natural interpretation.

These measures will be used in comparison with their respective from alternative specifications presented later on. The low values, however, are a warning sign that the model specification can be improved, by adding more explanatory variables and by altering the strict assumptions of logit.

4.2. Do we really need Mixed Logit?

As a pure logit, Model 1 will present all the significant drawbacks discussed in the Chapter 3. The specification proposed in Model 1, implies a uniform VTT for each stratum. In fact, by assuming a degenerate distribution for the coefficients of time and price, we automatically ignore the fact that VTT may significantly vary across members of the same stratum. In other words, we neglect heterogeneity. A *random coefficient model*, on the other hand, allows for a within-mode non-degenerate distribution of VTT (Chapter 3). We are interested in estimating the parameters that describe this distribution, and subsequently its moments.

Before specifying a *random coefficient model* (mixed logit), it might be a good idea to perform a Likelihood Ratio (LR) test to check for unobserved heterogeneity in the stratified samples. In other words we need to check the hypothesis that the coefficients are fixed against the alternative, that they are random across individuals. The following LR test is proposed in McFadden and Train (2000). A Lagrange Multiplier variant of this test is also available in Bolduc (2008).

Consider the choice from the set **C** = {L,R} and the vectors of attributes for the two alternatives $\mathbf{X}_L = (T_L, C_L, F_L)$ and $\mathbf{X}_R = (T_R, C_R, F_R)$. These attributes are the same as those used in Model 1 of section 4.1. From a random sample of N individuals we estimate the parameters for these attributes with logit. These are simply the ML estimates of the coefficients of Model 1.

The next step is to calculate the logit choice probabilities for the two alternatives:

$$\widehat{P}_L(x_L,\widehat{\beta}) = \exp[\widehat{V}_{rfL}] / \exp[\widehat{V}_{rfL}] + \exp[\widehat{V}_{rfR}] \quad \text{and}$$

$$\widehat{P}_R(x_R,\widehat{\beta}) = \exp[\widehat{V}_{rfR}] / \exp[\widehat{V}_{rfL}] + \exp[\widehat{V}_{rfR}] \qquad (4.5)$$

then we calculate the *auxiliary variables* for cost and time:

$$C^* = \sum_{j\in C_n} C_j \widehat{P}_j(x_j,\widehat{\beta}) = C_L \widehat{P}_L(x_L,\widehat{\beta}) + C_R \widehat{P}_R(x_R,\widehat{\beta}) \quad \text{and}$$

$$T^* = \sum_{j\in C_n} T_j \widehat{P}_j(x_j,\widehat{\beta}) = T_L \widehat{P}_L(x_L,\widehat{\beta}) + T_R \widehat{P}_R(x_R,\widehat{\beta}) \qquad (4.6)$$

And use them to construct the four *artificial variables*:

$$Z_{CL} = 0.5[C_L - C^*]^2,\ Z_{CR} = 0.5[C_R - C^*]^2,\ Z_{TL} = 0.5[T_L - T^*]^2 \text{ and } Z_{TR} = 0.5[T_R - T^*]^2 \qquad (4.7)$$

For each stratum, we add the *artificial variables* to Model 1 and estimate the following model:

$$V_{rfL} = \alpha + \beta_{time}TT_L + \beta_{\cos t}C_L + \beta_{fq}F_L + \gamma_{\cos t}Z_{CL} + \gamma_{time}Z_{TL} \quad \textbf{(Model 1')} \qquad (4.8)$$

$$V_{rfR} = \quad \beta_{time}TT_R + \beta_{\cos t}C_R + \beta_{fq}F_R + \gamma_{\cos t}Z_{CR} + \gamma_{time}Z_{TR}$$

We then use a likelihood ratio test for the hypothesis that the artificial variables Z should be omitted. The intuition behind the generation and inclusion of these artificial variables is that they are designed to 'catch' some sort of variance in the coefficients across individuals. For example, for a randomly selected individual with probabilities to select the left and right alternative $\widehat{P}_L(x_L, \widehat{\beta})$ and $\widehat{P}_R(x_R, \widehat{\beta})$ respectively, the auxiliary variables T^* and C^* represent the expected travel cost and travel time. The variable $0.5[T_L - T^*]^2$ then represents a type of taste variation around the mean.

Tables 4a and 4b summarize the BIOGEME estimates for the car, plane, bus and train sub-models. For α = 0.05 level of significance, the null hypothesis for zero gamma coefficients of the artificial variables is rejected in all sub-models except plane, for which the p-value of γ_{time} coefficient equals 0.10.

Table 4a: Estimation results for Model 1'

	CAR	PLANE	BUS	TRAIN
Coefficient				
constant	0.00369	-0.00201	0.09	0.0321
Robust Std. Err	0.0294	-0.0503	0.0353	0.0287
Robust t-test	0.13	-0.04	2.55	1.12
p-value	0.9	0.97	0.01	0.26
B_time	-0.0287	-0.0356	-0.00648	-0.0139
Robust Std. Err	0.00196	0.00458	0.00121	0.000943
Robust t-test	-14.65	-7.79	-5.35	-14.72
p-value	0	0	0	0
B_cost	-0.0175	-0.0127	-0.011	-0.0181
Robust Std. Err	0.00121	0.00179	0.00155	0.00114
Robust t-test	-14.48	-7.07	-7.12	-15.81
p-value	0	0	0	0
B_frequency	-0.147	-0.0034	0.000107	-0.000479
Robust Std. Err	0.025	0.000722	0.00013	0.000354
Robust t-test	-5.86	-4.71	0.82	-1.35
p-value	0	0	0.41	0.18
γ_cost	0.0000483	0.0000174	0.0000571	0.0000822
Robust Std. Err	0.0000121	5.27E-06	0.0000237	0.0000105
Robust t-test	3.98	3.31	2.41	7.83
p-value	0	0	0.02	0
γ_time	0.000123	0.0000623	0.0000467	0.000071
Robust Std. Err	0.0000206	0.0000383	0.000018	0.00000874
Robust t-test	5.95	1.63	2.59	8.12
p-value	0	0.1	0.01	0

Table 4b: summary statistics for Model 1'				
	CAR	PLANE	BUS	TRAIN
Null log-likelihood	-4570.613	-1603.249	-2744.863	-4219.88
Initial log-likelihood	-4570.613	-1603.249	-2744.863	-4219.88
Final log-likelihood	-3813.132	-1397.624	-2568.437	-3671.749
Likelihood ratio test	-1514.96	411.25	-352.852	1096.263
Rho-square	0.166	0.128	0.064	0.13
Adjusted Rho-square	0.164	0.125	0.062	0.128
Nr of observations	6594	2313	3960	6088

We now perform a *Likelihood Ratio test* for the null hypothesis that Model 1 is the real model, that is, the coefficients of both artificial variables are zero, against the alternative which suggests that Model 2 with artificial variables is superior.

H_0: $\gamma_{cost} = \gamma_{time} = 0$

The Likelihood Ratio is:

$$\Lambda = \frac{lik_{H_0}(\widehat{\beta}_{mle})}{lik_{H_1}(\widehat{\beta}_{mle})} \qquad (4.9)$$

And the test statistic: $-2\log\Lambda = -2[\log lik_{H_0}(\widehat{\beta}_{mle}^{H_0}) - \log lik_{H_1}(\widehat{\beta}_{mle}^{H_1})] = -2[L(\widehat{\beta}_{mle}^{H_0}) - L(\widehat{\beta}_{mle}^{H_1})]$ is asymptotically χ^2 distributed with 2 degrees of freedom. The critical value for $\alpha = 0.01$ is 9.21. The test rejects the null hypothesis for all sub-models as shown in the test summary below.

Table 5: Generalized Likelihood Ratio Test Summary			
REFERENCE TRANSPORT MODE	Log-likelihood under H0 (Model 1)	Log-likelihood under H1 (Model 1')	Generalized Likelihood Ratio
CAR	-3909.986	-3813.132	193.708
PLANE	-1414.685	-1397.624	34.122
BUS	-2579.592	-2568.437	22.31
TRAIN	-3751.855	-3671.749	160.212

This Likelihood Ratio test is asymptotically equivalent to a Lagrange Multiplier test for the hypothesis of no mixing against the alternative of mixed logit with randomized time and cost coefficients as proved by McFadden and Train (2000).

The above test gives 'the green light' to the researcher to move further and specify a mixed logit model with random time and cost coefficients. It does not, however, suggest which mixing distribution should be used. Neither does it imply an optimal modeling option for the interests of the researcher. Actually, the idea of a jointly mixed logit (when both cost and time coefficients are random) is associated with a higher computational cost of VTT. These issues are discussed in the next sections, in which we take the first step to mixed logit.

4.3. Which parameters should be random?

The Likelihood Ratio test by McFadden and Train suggests that both time and cost partworths (coefficients of utility function) should be modeled as random across individuals. Modeling both of them as random would be the most realistic case. Nevertheless, there are serious reasons to model only one of them –the time coefficient- as probabilistic and keep the other one-the cost coefficient- fixed.

Assigning a joint distribution to b_{cost} and b_{time} involves accommodating the correlation between them, which may not be an easy task. Second, the method of parametric estimation in mixed logit models, *Maximum Simulated Likelihood*, involves draws from the bivariate distribution $f(\beta_{\cos t}, \beta_{time})$ in order to approximate the mixed logit choice probability:

$$P(i) = \int_{\beta_{\cos t}} \int_{\beta_{time}} \Lambda(i \mid \beta_{\cos t}, \beta_{time}) f(\beta_{\cos t}, \beta_{time}) d\beta_{time} d\beta_{\cos t}.$$

In many cases this might be an additional complication, depending on the assumptions about the joint pdf (probability distribution function) of the partworths.

Also, the distribution of VTT, that is the distribution of the ratio of β_{time} on $\beta_{\cos t}$, might be unknown. Since the interest of this study is concentrated on VTT, the assumption of non-random $\beta_{\cos t}$ facilitates the modeling of VTT distribution. Consider the case where β_{time} follows a normal distribution with mean μ and standard deviation σ, [$\beta_{time} \sim N(\mu_{\beta_t}, \sigma_{\beta_t})$], and $\beta_{\cos t}$ is constant.

Then, $\beta_{time} / \beta_{\cos t} = VTT \sim N(\frac{\mu_{\beta_t}}{\beta_c}, \frac{\sigma_{\beta_t}}{\beta_c})$. It is therefore possible to estimate the mean and the standard deviation of VTT by estimating the cost coefficient and the mean and the standard deviation of the random time coefficient. Thus, for the remaining it is going to be assumed that only β_{time} is random. Its probability distribution function is called the *mixing distribution*. The choice of this density function is the topic of the next section.

4.4. Which 'mixing distribution' to use?

Distributions are essentially arbitrary approximations to the real *behavioral profile*. 'We select specific distributions because we have a sense that the empirical truth is somewhere in their domain' (Hensher & Greene,2001: pp.146). This study experiments on the Normal, Log-Normal and Johnson's S_B distribution as mixing distributions.

The most commonly used distribution in mixed logit models is the Normal, mainly because of its low computational cost. On the other hand, the fact that the domain of the Normal density function is the entire real line means that some of the mass of the VTTS will inevitably fall on the negative side. The implicit assumption of the model is that negative values of travel time savings (or, equally, positive values of travel time) exist in the population with some probability that depends on the estimated parameters of the normal distribution.

If data allows for such a possibility, then Normal is able to reveal this effect, and is in fact a good mixing distribution for time coefficients. 'The issue with the Normal distribution is thus the problem of deciding whether a non-zero probability of a positive coefficient is *revealed* by data or is simply an artifact of the symmetrical nature of the distribution' (Hess et al., 2005). The data used in this study *do not allow for negative VTTS*; the unbounded nature of the normal distribution just 'forces' the model to produce negative VTTS (positive VTT). Model 2 introduced in section 4.5 uses Normal as a mixing distribution. An example with Normal mixing distribution for the time coefficients can be found in Algers et al. (1998).

Truncated mixing distributions is a possibility that has been discussed in the literature by Hensher and Greene (2003), Train and Sonnier (2004) and Train (2002). By truncating the Normal distribution of time coefficient at zero, the researcher can constrain VTTS to take only positive values. Despite being a promising development for the future, Truncated Normal is excluded from this study since BIOGEME 1.5, has not incorporated it yet.

Nevertheless, the same software allows for MSL estimation with other *bounded mixing distributions*, as long as they are transformations of Normal. We use a semi-bounded distribution with fixed lower bound at zero, namely the Lognormal (Model 3) and a two-side bounded with flexible upper and lower bound, namely the Johnson S_B (Model 4). The former has been used in the literature to model random coefficients with unambiguous signs, such as price. Train and Sonnier (2004) compare a model with a joint Normal mixing distribution for its random coefficients to a counterpart in which partworths follow the Lognormal, in the context of a vehicle choice study. The model with Lognormal mixing distribution showed a substantially higher log-likelihood than its Normal counterpart.

The main disadvantage of Lognormal distribution is its thick tail. The behavioral implication of the thick tail is the existence of obscurely high WTP for time savings for some share of the population. As in the case of Normal distribution, extremely high WTP may, or may not be supported by data. The justification of Lognormal as a good mixing distribution depends on whether the sample exhibits the above property. Model 3 in section 4.6 uses Log-Normal as mixing distribution.

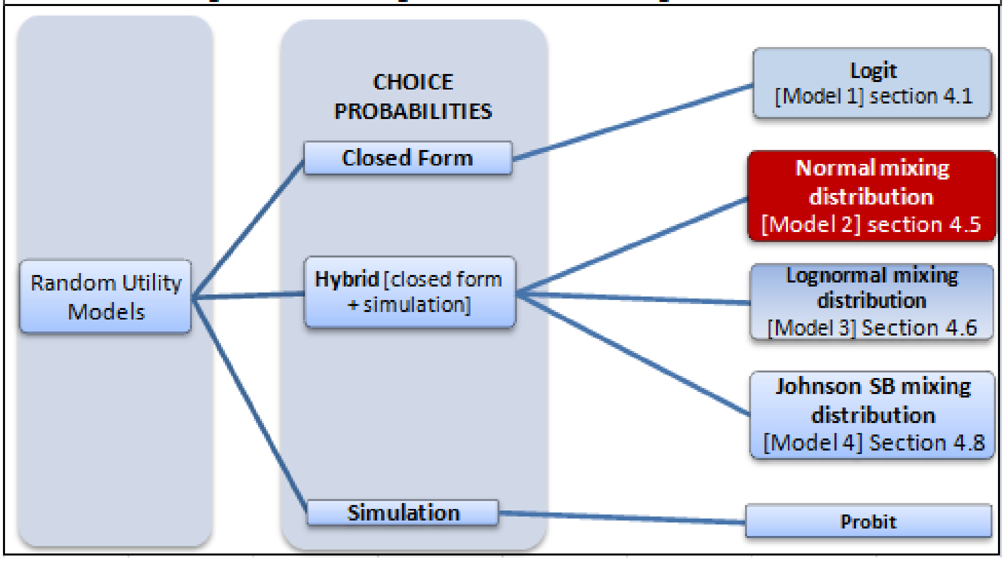
The mixing distribution used in models 4a and 4b is the Johnson S_B. Its main advantage lies in its flexibility. Either both bounds can be fixed ex ante and the mean and standard deviation can be estimated by MSL (section 4.9) or one of the bounds can be fixed ex ante and the rest of the three parameters can be estimated by MSL (section 4.8). Setting both bounds as random parameters for estimation involves simulation with a sort of *quasi-random draws*, *Gibbs sampling* (Train, 2002: pg.215). This goes beyond the scope of this study. The distribution is very flexible and can take lots of shapes, depending on its range (Johnson1994: pg.37).

The use of Johnson S_B as mixing distribution is relatively recent and encouraged in literature. Train and Sonnier (2004) fix the lower bound at zero and the upper bound at a value 'high enough to accommodate nearly all the cumulative distribution function' of Log-normal. The S_B provided a 'plateau' shape distribution that Log-normal cannot produce and the log-likelihood increased significantly. Hess et al. (2005) used the S_B and compared it to models with Normal and Log-normal mixing distribution. Unfortunately, recovering the S_B moments from the moments of a Normal distribution is not an easy task. Methods for the calculation of the S_B moments are presented in Johnson et al. (1994, pg. 35). Another solution would be simulation; to use the normal invert cdf, in order to draw observations from the S_B distribution and approximate its moments. This is how VTTS estimates are obtained for models 4a and 4b in sections 4.8 and 4.9 respectively.

Another possibility is the Triangular distribution. It is rarely used in hybrid contexts, mainly because of its linear tails. However, it theoretically overcomes the drawbacks of Normal and Log-Normal; its bounds prevent negative VTTS or extremely high WTP. Nevertheless, neither Hess et al. (2005) nor Train and Sonnier (2004) incorporate Triangular in their models. An empirical comparison between mixing distributions containing Triangular can be found in Hensher and Greene (2003).

4.5. Normally distributed time coefficient

Figure I: Mixed logit with Normal mixing distribution



We now specify a model with a random time coefficient that is assumed to follow the normal distribution.

$$V_{nL} = \alpha + \beta^{n}_{time} TT_L + \beta_{cost} C_L + \beta_f F_L$$

$$V_{nR} = \beta^{n}_{time} TT_R + \beta_{cost} C_R + \beta_f F_R \quad \textbf{(Model 2)} \qquad (4.10)$$

where $\beta^{n}_{time} \sim N(\mu, \sigma)$ and β_{cost}, β_f are generic and fixed in the population. Like the models of the previous sections, Model 2 is applied to four strata; choices are between L and R in a *within-mode* context. MSL estimation has been carried out sequentially in four steps; initially with 100 *pseudo-random draws*, then by using these results as starting values an estimation with 250 draws followed. The process was repeated for 500 draws and the results were used as starting values for the final estimation with 1000 draws. The improvements in terms of fit and final log-likelihood in comparison with Model 1 are remarkable. Table 6a summarizes the estimation results for Model 2.

All alternative specific constants are highly insignificant (p-values bigger than 0.1) except for the bus sub-model in which it is insignificant at $\alpha = 0.01$. Frequency is also insignificant for the same mode. The rest of the coefficients are significantly different than zero. These facts are generally in accordance with Model 1 (pure logit). The 95% upper and lower percentile limits are the values of β_{time} for which the associated cdf of the fitted distribution equals 0.95 and 0.05 respectively.

Table 6a: Estimation results for Model 2

Coefficient	Sub-Model 2a: CAR	Sub-Model 2b: PLANE	Submodel 2c: BUS	Sub-Model 2d: TRAIN
B_TIME	-0.0481	-0.057	-0.00767	-0.0234
Robust Std Err.	0.00318	0.00742	0.00139	0.00247
Robust t-test	-15.4	-7.68	-5.52	-9.5
SIGMA_TIME	0.0446	0.05	0.0145	0.0276
Robust Std Err.	0.00329	0.0628	0.00159	0.00285
Robust t-test	13.55	7.96	9.12	9.71
Upper 95% percentile limit	0.025260472	0.025242681	0.016180378	0.02199796
Lower 95% percentile limit	-0.121460472	-0.139242681	-0.031520378	-0.06879796
B_COST	-0.0233	-0.0141	-0.0103	-0.0186
Robust Std Err.	0.00203	0.0028	0.00132	0.00167
Robust t-test	-11.5	-5.03	-7.79	-11.1
B_FREQ	-0.174	-0.00449	7.00E-05	-0.00112
Robust Std Err.	0.0301	0.00106	0.00014	0.000493
Robust t-test	-5.78	-4.25	***0.5	*-2.26
Constant	-0.0306	-0.00253	0.0953	0.0381
Robust Std Err.	0.0349	0.0561	0.0381	0.032
Robust t-test	***-0.88	***-0.05	*2.5	***1.19
Nr. of observations	6594	2313	3960	6088

*= not significant in 0.01 **=not significant in 0.05 ***=not significant in 0.1

Table 6b presents the estimates of the parameters of the VTTS distribution, which are functions of the estimates of $\widehat{\beta}_{cost}$, $\widehat{\mu}$ and $\widehat{\sigma}$. The mean VTTS estimates from Model 2 are higher than the uniform VTTS estimates of Model 1. This contradicts the results of Algers et al. (1998) where mean VTTS estimates in a random time coefficient model with fixed cost coefficient for pooled (WTP and WTA samples) data are lower than those from a classic logit. On the other hand, Hess et al. (2005) estimated VTTS to be much higher with a mixed logit model than with pure logit.

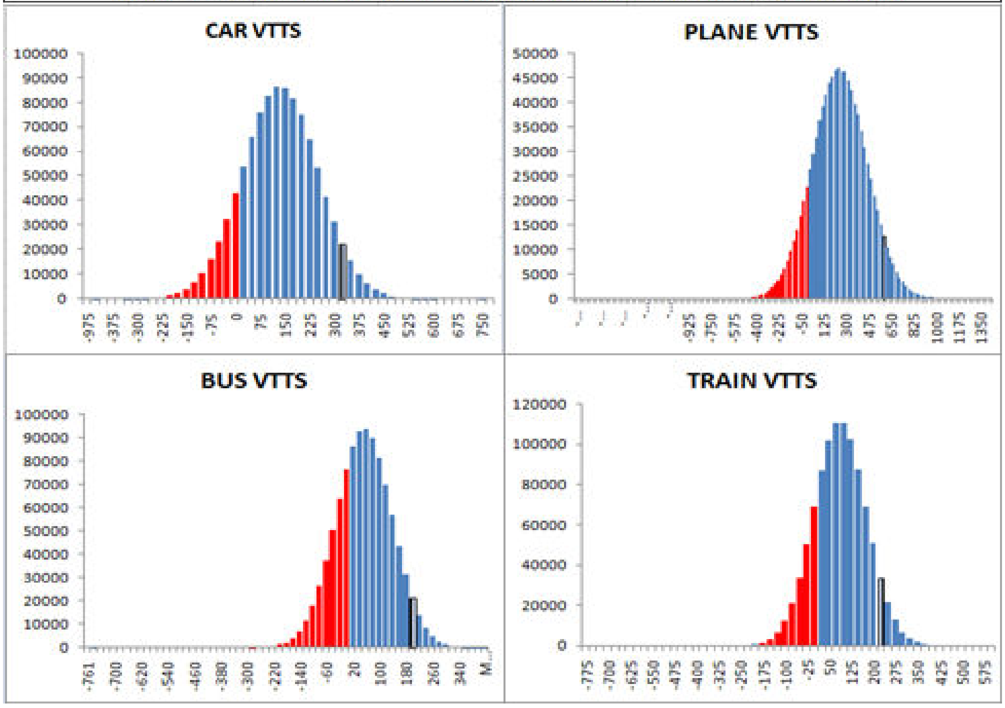
Table 6b: Estimated VVTS and summary statistics for Model 2				
	Sub-Model 2a: CAR	Sub-Model 2b: PLANE	Submodel 2c: BUS	Sub-Model 2d: TRAIN
Mean VTTS	**2.064**	**4.043**	**0.7447**	**1.258**
Robust Std Err.	0.1297	0.5759	0.1057	0.1061
Robust t-test	15.91	7.019	7.044	11.85
p-value	0	0	0	0
Std VTTS	**1.914**	**3.546**	**1.408**	**1.484**
Robust Std Err.	0.1462	0.615	0.1975	0.1309
Robust t-test	13.09	5.766	7.126	11.34
p-value	0	0	0	0
Mean VTTS in NOK	**123.84**	**242.58**	**44.682**	**75.48**
95% upper quantile limit	5.212249842	9.875650961	3.060653907	3.698962782
95% upper quantile limit in NOK	312.7349905	592.5390577	183.6392344	221.9377669
Prob VTTS < 0	0.1401	0.1271	0.2981	0.1977
Null Log-Likelihood	-4570.613	-1603.249	-2744.863	-4219.88
Final Log-Likelihood	-3410.891	-1329.414	-2507.08	-3462.56
Likelihood Ratio test	2319.443	547.67	475.565	1514.64
Rho-square index	0.253	0.168	0.085	0.178

Based on the fitted VTTS distribution, estimates of the 95% upper quantile limit are presented in Table 6b. These estimates are the implied price limits that ‘cover’ 95% of the population’s WTP for time savings in NOK per minute and per hour. The model implies for instance, that 95% of the car drivers (sub-model 3a) are willing to pay up to 312.73 NOK to reduce driving time by one hour. The other side of the same coin is that 5% of the car drivers are willing to pay *more* than 312.73 NOK to save one hour of driving time.

The probability that VTTS is negative is neither supported by economic theory, nor is built in the data, since the design of the questionnaire does not allow for such a possibility. Despite this, the Normal distribution as a model forces VVTS to take both positive and negative values. The value of the fitted Normal cumulative distribution function at zero equals the estimated probability of negative VTTS. Therefore, the sub-models’ estimates (wrongly) imply that 14.01% of car drivers, 12.71% of plane passengers, 29.81% of bus passengers and 19.77% of train passengers are willing to pay for a longer trip time.

To have a visual image of these aspects, the VTTS distributions for the four sub-models have been simulated with 1000000 draws each. The images are given in Figure J. The red part of the mass represents the simulated probability of negative VTTS, while the dark shadow on the right tail is the simulated 95% upper quantile limit.

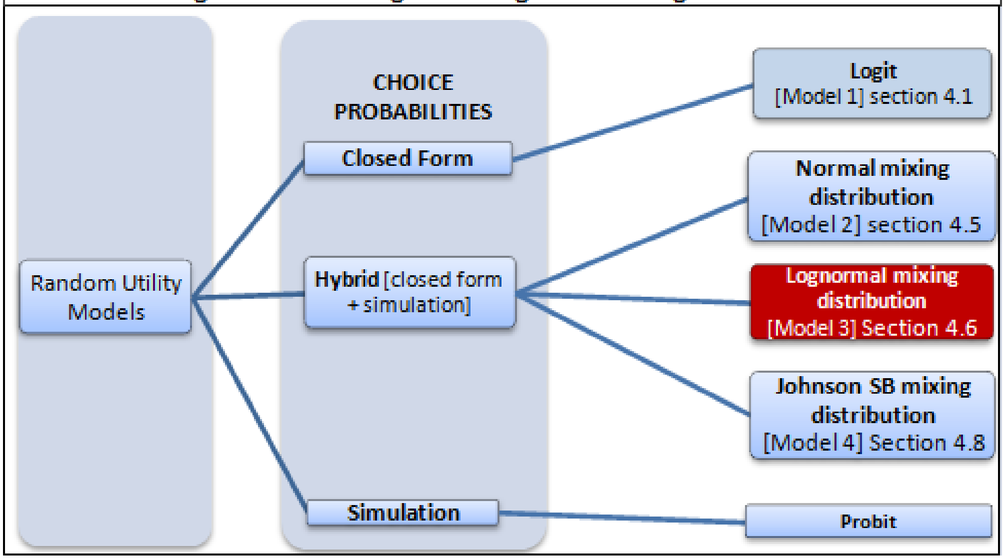
Figure J: Simulated Normal VTTS distributions with 1000000 draws



This wrong behavioral implication is the main disadvantage of the normal distribution. The next model introduces the Lognormal as mixing distribution. As a model, Lognormal solves the above problem by ‘forcing’ VTTS to be non-negative. On the other hand, one other peculiarity arises, associated with the unbounded thick tail of the distribution, which may imply extremely high VTTS for a significant share of the population.

4.6. Log-Normally distributed time coefficient

Figure K: Mixed logit with Logormal mixing distribution



A model in which $VTTS \sim LN(\mu - \ln \beta_{cost}, \sigma)$ can be specified from:

$$V_{nL} = \alpha - \zeta^{n}_{time} TT_L + \beta_{cost} C_L + \beta_{freq} F_L \quad \textbf{(Model 3)}$$

$$V_{nR} = \quad - \zeta^{n}_{time} TT_R + \beta_{cost} C_R + \beta_{freq} F_R \qquad (4.11)$$

where ζ is an exponentiated pseudo-random draw from a Normal distribution with parameters μ and σ, such that $\zeta_n = e^{\beta_n}$. All sub-models of Model 3 were estimated sequentially in two steps. First, MSL estimation was carried out for 100 pseudo-random draws and the estimates were used as initial values in the second step, where MSL estimation was repeated for 1000 Lognormal draws. Table 7a shows the estimation results for Model 3.

As in Model 2, alternative specific constants in all sub-models are not different than zero at all convenient levels of significance apart from the alternative specific constant in the bus sub-model, which is not zero at α = 0.01. The estimates of μ and σ are highly significant. The mean and the standard deviation of the associated Lognormal distribution are functions of these parameters given by Train (2002: pp. 209) and Johnson et al. (1994). These are:

- $E(\zeta) = \exp[\mu_\beta + (\sigma^2_\beta / 2)]$ and
- $Sd(\zeta) = \sqrt{\exp(2\mu + \sigma^2)[\exp(\sigma^2) - 1]}$. (4.12)

Table 7a: Estimation results for Model 3				
Coefficient	Sub-Model 4a: CAR	Sub-Model 4b: PLANE	Submodel 4c: BUS	Sub-Model 4d: TRAIN
B_TIME	-3.57	-3.33	-5.69	-4.83
Robust Std Err.	0.062	0.127	0.243	0.167
Robust t-test	-57.62	-26.26	-23.4	9.13
SIGMA_TIME	1.16	1.16	0.995	2.51
Robust Std Err.	0.0844	0.181	0.197	0.275
Robust t-test	13.8	6.38	5.05	9.13
B_COST	-0.0199	-0.0138	-0.00825	-0.0191
Robust Std Err.	0.00145	0.00184	0.000836	0.00161
Robust t-test	-13.7	-7.5	-9.86	-11.85
B_FREQ	-0.169	-0.0045	0.000175	-0.00102
Robust Std Err.	0.0268	0.000747	0.000097	0.000396
Robust t-test	-6.3	-6.02	**1.81	*-2.58
Constant	-0.0124	-0.00985	0.0835	0.0461
Robust Std Err.	0.0318	0.0514	0.0339	0.0345
Robust t-test	***-0.39	***-0.19	*2.47	***1.34
Nr. of observations	6594	2313	3960	6088

All cost coefficients are statistically significant and have the expected (negative) sign. Like in previous models, the frequency coefficient is insignificant at $\alpha = 0.05$ for bus and at $\alpha = 0.01$ for train. Table 7b presents the estimation results concerning VTTS, and the summary statistics.

Table 7b: Estimation results for Model 3				
	Sub-Model 3a: CAR	Sub-Model 3b: PLANE	Submodel 3c: BUS	Sub-Model 3d: TRAIN
Mean VTTS	**2.772738742**	**5.082924001**	**0.67203462**	**9.758287695**
Std Err. VTTS	**4.673105588**	**8.566634928**	**0.873981412**	**227.5222508**
Mean VTTS in NOK/h	**166.3643245**	**304.9754401**	**40.32207722**	**585.4972617**
95% upper quantile limit VTTS	9.535920317	17.48104051	2.104696839	25.96240545
95% quantile limit in NOK per hour	572.155219	1048.862431	126.2818104	1557.744327
Simulated Mean VTTS (20000 draws)	2.790868258	5.10656017	0.676151243	9.50529686
Simulated Std Err. (20000 draws)	4.607441804	8.707927557	0.866583179	85.3224315
Simulated mean VTTS (20000 draws)/h	167.4520955	306.3936102	40.56907458	570.3178116
Simulated 95% upper quantile limit VTTS	9.262100143	17.49514218	2.099359792	25.75840011
Null Log-Likelihood	-4570.613	-1603.249	-2744.863	-4219.88
Final Log-Likelihood	-3793.808	-1393.374	-2577.696	-3656.885
Likelihood Ratio test	1553.608	419.752	334.334	1125.989
Adj. Rho-square index	0.169	0.128	0.059	0.132
*= not significant in 0.01 **=not significant in 0.05 ***=not significant in 0.1				

The mean and standard error VTTS are calculated using (4.12). The estimated VTTS for car and plane in this model are higher compared to the estimates from the model with Normal mixing distribution. This is in accordance with the study of Hess et al. (2005) in which the mean Lognormal VTTS is higher than the Normal; and also with Hensher and Greene (2003) in which the mean Lognormal VTTS estimates are more than three times higher than the mean VTTS estimated from an mixed logit with Normal mixing distribution. On the other hand, VTTS for bus passengers is slightly lower than its respective from Model 2.

The most remarkable result is the *unexpectedly high VTTS estimate for train passengers*, which is almost eight times the VTTS estimate from the model with Normal mixing distribution. This may look odd at first sight, but can be explained by the high standard deviation estimate; the model estimates that $\mu = -4.83$ and $\sigma = 2.51$. Both the mean and the standard deviation of lognormal density are exponentially increasing in μ and σ. Also, by definition the mean of Lognormal is a function of both μ and σ. By moment transformation, a Log-normally distributed time coefficient has a mean of 9.758 and a standard deviation of 227.522 (Table 7b). High value of σ produces a very long, thick right tail. This suggests that quite often an extraordinarily high value will be drawn from this density, pushing the mean to higher values. The implication is that Lognormal is not a good model when observations are quite diverse, as in the train sub-model.

The 95% quantile limit is the invert VTTS cumulative distribution function evaluated at 0.95. This is the WTP for travel time savings that 'covers' 95% of the population. It also implies that there is still a 5% share of drivers or passengers whose willingness to pay is higher than this value. This value is 572 NOK/h for car drivers and 1049 NOK/h, 126 NOK/h, 1558 NOK/h for plane, bus and train passengers respectively. Again, the peculiarity of the estimate for train lies in the high underlying σ.

The moments of the Lognormal distribution of the time coefficient can also be approximated by simulation. Using the estimates of μ and σ, we draw 20000 observations from N(μ,σ) and exponentiate them. The transformed observations follow the Lognormal distribution and their average is the *simulated mean* while their standard deviation is the *simulated standard error*. From Table 7b we see that the 'simulated mean VTTS' for all sub-models are quite close to the approximate means of the first line. The close relation also holds for the simulated and estimated standard errors, except for the train case, in which the simulated standard error is significantly smaller, approximately 85.3, against 227.5 which is the estimate we obtain by transformation.

The simulated 95% upper quantile limits were obtained by drawing 20000 observations from a Lognormal with $\widehat{\mu}_{MSL}$ and $\widehat{\sigma}_{MSL}$, rank them, and observing the cut-off value of the 19000-th observation. These values are generally consistent with the values obtained by the Lognormal cdf.

The final log-likelihoods are lower than those from the Normal mixing distribution model (Model 2) for all sub-models, but still higher than those from logit model (Model 1). The *likelihood ratio test* is high enough to reject the null hypothesis under which all coefficients are zero. The *likelihood ratio index* (adjusted ρ^2) is also higher than the logit model's but lower than the mixed logit model's with Normal mixing distribution, for all sub-models.

4.7. A bootstrap experiment

An insight into the inherent variability of the maximum simulated likelihood estimates of VTTS can be given with *bootstrap*, which is a recent development in statistics used to approximate the unknown sampling distribution of the estimated parameters of a distribution. We apply it to compare the estimated moments (mean and standard deviation) in the sub-models for car and train under Lognormal mixing distribution of time coefficients. For these two modes 1000 samples, with 1000 observations each, drawn from a Lognormal distribution with parameters $\widehat{\mu}_{MSL}$ = -4.83, $\widehat{\sigma}_{MSL}$ = 2.51 for train and $\widehat{\mu}_{MSL}$ = -3.57, $\widehat{\sigma}_{MSL}$ = 1.16 for car are generated (the true μ and σ are unknown). In other words, we repeat the simulation process 1000 times. The aim is to check the stability of the estimates across the samples.

For each 1000-sample the empirical lognormal mean and standard deviation is estimated (denote them by ε_i^* and ω_i^* respectively for the i-th 1000-sample), such that a set of 1000 vectors $(\varepsilon_i^*, \omega_i^*)$ is obtained. The average values $\overline{\varepsilon}$ and $\overline{\omega}$, which are then given by $\overline{\varepsilon} = \frac{1}{1000}\sum_1^{1000} \varepsilon_i^*$ and $\overline{\omega} = \frac{1}{1000}\sum_1^{1000} \omega_i^*$ will be biased towards the mean and the standard deviation of a lognormal density with parameters $\widehat{\mu}_{MSL}$ and $\widehat{\sigma}_{MSL}$, that is towards 9.758 and 227.522 for train and 2.773 and 4.673 for car (Table 7b). The standard errors however, which are given by $s_{\varepsilon^*} = \sqrt{\frac{1}{1000}\sum_1^{1000}(\varepsilon_i^* - \overline{\varepsilon})}$ and $s_{\omega^*} = \sqrt{\frac{1}{1000}\sum_1^{1000}(\omega_i^* - \overline{\omega})}$ are concise quantifications of the amount of variability of the estimates of the lognormal mean and standard deviation. Bootstrap is described in Rice (2003).

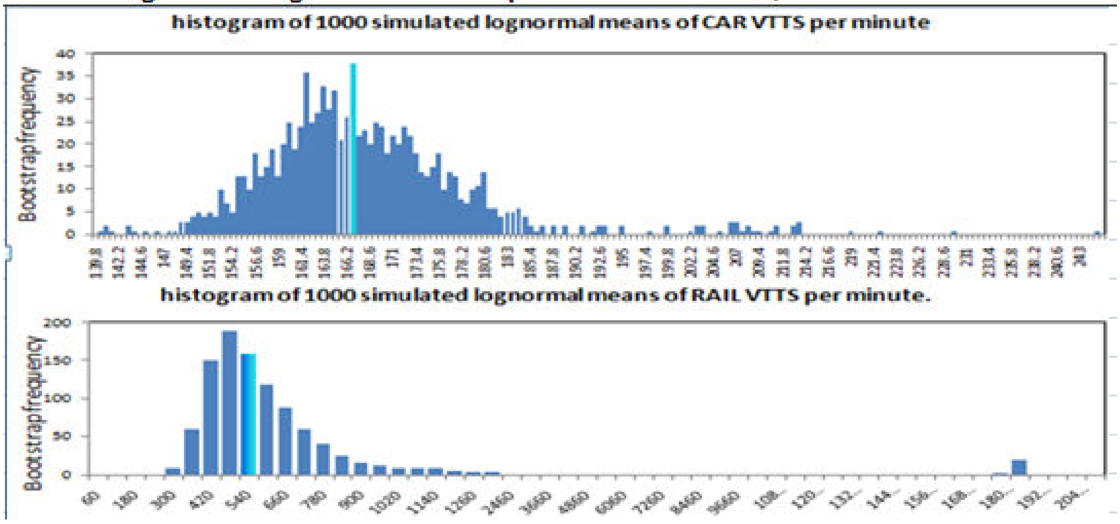
The results are given in Table 8. In the case of car, the bootstrap VTTS per minute and the bootstrap standard deviation of VTTS per minute are close to the estimates of Table 7b. The standard error of the bootstrap mean shows the variability of the estimate across samples of 1000 observations. Its small value renders the simulated mean VTTS in table 7b a reliable estimate. On the other hand, the variability of the bootstrap standard error of VTTS in car is not negligible, so the observer should be tentative when utilizing the estimates of standard deviation.

Table 8: Bootstrap experiment. Results from 1000 generated samples of 1000 observations each.

Mode	CAR	TRAIN
Boostrap mean VTTS per minute(1000 samples)	2.798704269	15.96382377
standard error	0.192143038	44.27150897
Bootstrap Std. Error of VTTS(1000 samples)	5.123016882	288.0273534
standard Error	3.362113822	1384.908208

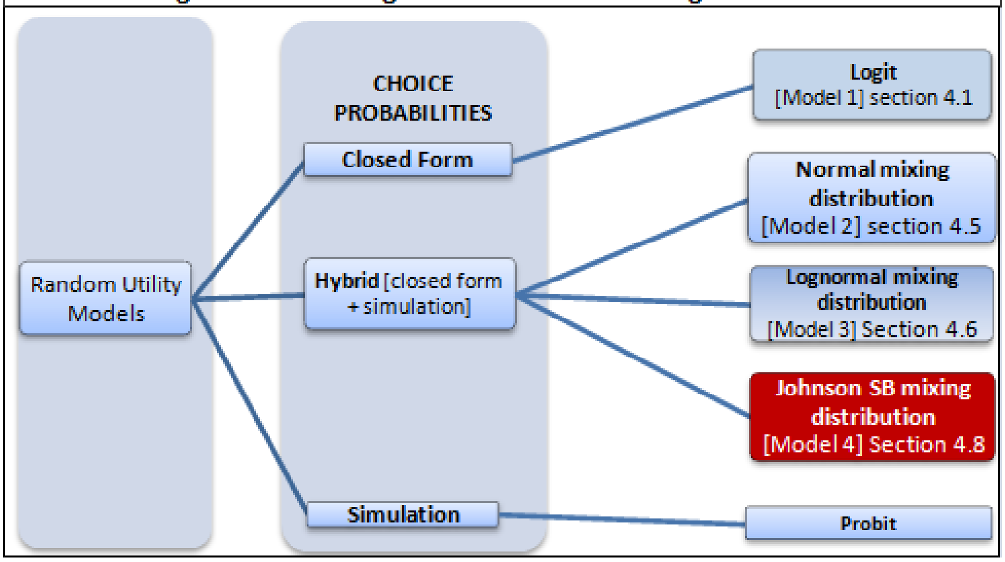
In the case of train, the enormous variability of both the bootstrap mean and standard error, suggests that we cannot rely on the estimates of Table 7b when assessing VTTS for train passengers. This may in turn imply that Lognormal is not a good model for VTTS when *data are not informative* as in sub-model 3d. Figure L shows the two histograms that display the difference in the variability of the means for car and train.

Figure L: Histograms of 1000 sample mean VTTS in NOK/h for car and train



4.8 *Johnson S_B distributed time coefficient*

Figure M: Mixed logit with Johnson SB mixing distribution



We now turn to a relatively new and very interesting type of mixing distribution, namely the Johnson S_B distribution (Johnson et al., 1994). If the time coefficient is normally distributed, the transformation:

$$\xi^{n}_{time} = \lambda + (\nu - \lambda)\{\frac{\exp(\beta_{time})}{[1+\exp(\beta_{time})]}\} \qquad (4.13)$$

is said to follow the Johnson S_B distribution where λ is the lower cut-off point and $(\nu-\lambda)$ the range. Since β_{time} is normally distributed, $\frac{\exp(\beta_{time})}{[1+\exp(\beta_{time})]}$ belongs to the open interval (0,1). It follows that ξ^n_{time} defined in (4.13) belongs to the interval (λ,ν). It is a requirement that λ is non-negative. The specification for the within mode choice Model 4 is:

$$V_{nL} = \alpha - \xi^n_{time} TT_L + \beta_{\cos t} C_L + \beta_{freq} F_L$$

$$V_{nR} = \quad -\xi^n_{time} TT_R + \beta_{\cos t} C_R + \beta_{freq} F_R \quad \textbf{(Model 4)} \qquad (4.14)$$

The estimation was carried out at once with 500 draws, without prior values, except for the car sub-model, in which initial values from an estimation process with 200 draws were used. The lower bound of the time coefficient, and hence the *minimum WTP to save time*, was *fixed to zero*. The upper bound was set to be a free parameter and then estimated for the four transport modes. The reader must bear in mind that the use of Johnson S_B in this study is purely experimental, mainly because of a relative scarcity of other applications and examples in VTTS bibliography. Thus, despite sensible, the results of this section must be taken into account tentatively. Table 9a presents the results of the estimation.

Table 9a: Estimation results and summary statistics for Model 4

Coefficient	Sub-model 4a: CAR	Sub-model 4b: PLANE	Sub-model 4c: BUS	Sub-model 4d: TRAIN
B_TIME	2.6	-1.09	-4.67	-3.26
Robust Std. Err	2.8	1.34	21.1	0.557
Robust t-test	***0.93	***-0.82	***-0.22	-5.86
SIGMA_TIME	7.76	2.03	11.9	6.09
Robust Std. Err	5.19	1.35	45.1	2.18
Robust t-test	***1.49	***1.5	***0.26	*-2.79
B_COST	-0.0211	-0.014	-0.00881	-0.0195
Robust Std. Err	0.00144	0.00181	0.000893	0.00157
Robust t-test	-14.62	-7.7	-9.87	-12.42
B_FREQ	-0.172	-0.00437	0.000153	-0.000907
Robust Std. Err	0.0273	0.000725	0.000121	0.0004
Robust t-test	-6.3	-6.03	***1.27	*-2.27
UPPER BOUND	0.0667	0.162	0.0171	0.115
Robust Std. Err	0.00863	0.128	0.00674	0.0217
Robust t-test	7.72	***1.26	*2.54	5.31
Constant	-0.0206	-0.014	0.0856	0.0474
Robust Std. Err	0.0327	0.0517	0.0347	0.0348
Robust t-test	***-0.63	***-0.27	*2.47	***1.36
Null log-likelihood	-4570.613	-1603.249	-2744.863	-4219.88
Final log-likelihood	-3765.219	-1390.886	-2575.436	-3651.645
Likelihood Ratio test	1610.787	424.727	338.853	1136.471
Adj. Rho-square index	0.175	0.129	0.06	0.133
Nr. of observations	6594	2313	3960	6088
*= not significant in 0.01 **=not significant in 0.05 ***=not significant in 0.1				

The μ and σ coefficients appear to be not significant at $\alpha = 0.1$ for the car, plane and bus sub-models. On the other hand, the same coefficients are significant at $\alpha = 0.05$ in the model for train. The cost coefficients are significant in all modes, and have the expected negative sign. As in previous model estimations, frequency appears to be insignificant in the bus sub-model and not significant at $\alpha = 0.01$ in the rail sub-model. All alternative specific constants are insignificant, except for bus in which the constant remains significant at $\alpha = 0.05$.

The new estimate is the upper bound of the time coefficient distribution. This value divided by the negative of the cost coefficient, gives the maximum WTP for time savings in a specific transport mode. The estimates of the upper bound are significant at $\alpha = 0.05$, apart from the plane sub-model.

The fit of the model is lower that the fit provided by the model with Normal mixing distribution, but higher than its Lognormal counterpart; the adjusted ρ^2 index of Model 4 is higher compared to Model 3, for all sub-models. The same result holds, when comparing the likelihood ratio tests of the Models 2-4.

The moments of the Johnson S_B distribution are not a closed form expression of the parameters μ and σ, so recovering them by the estimates is not an easy task. Nevertheless, the mean and the standard deviation of the time coefficient can be approximated by simulation. For each sub-model, 20000 observations were drawn from a Normal distribution with the estimates for μ and σ as parameters. These observations were transformed into 20000 Johnson S_B observations, by using the estimated upper bound in each mode. The average of this 20000-sample is the simulated mean and its standard deviation is the simulated standard deviation.

Table 9b presents the simulated estimates. For car, bus and train sub-models the simulated VTTS estimates are higher than the corresponding from logit model but lower than the same estimates from the other mixed logit models. For the rail sub-model, the VTTS estimate exceeds its estimated value from the model with Normal mixing distribution, but is still way smaller than the unrealistic estimate from the model with Lognormal mixing distribution. The upper bound VTTS is the estimated maximum willingness-to-pay for time savings in a given mode.

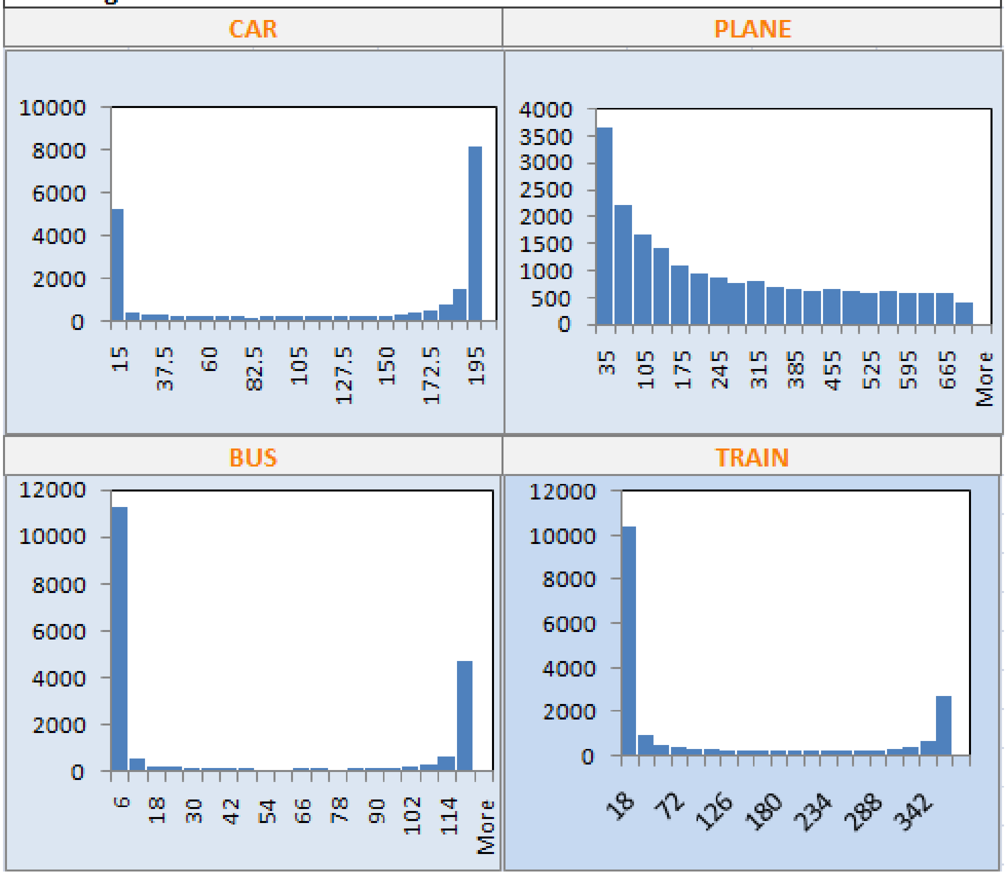
Table 9b: Simulated VTTS and maximum WTP for Model 4.

	Sub-model 4a: CAR	Sub-model 4b: PLANE	Sub-model 4c: BUS	Sub-model 4d: TRAIN
Simulated mean time coefficient	0.041740641	0.055166735	0.005909062	0.035087596
Simulated MeanVTTS per min	1.978229427	3.940481077	0.670722129	1.799363909
Simulated Mean VTTS per hour	**118.6937656**	**236.4288646**	**40.24332771**	**107.9618346**
Simulated variance	0.000829072	0.002289821	5.72663E-05	0.002069903
Simulated standard deviation	0.028793606	0.04785207	0.007567448	0.04549619
Simulated Std VTTS per min	1.364625888	3.418004984	0.858961208	2.333137929
Upper bound VTTS per min	3.161137441	11.57142857	1.940976163	5.897435897
Upper bound VTTS per hour	**189.6682464**	**694.2857143**	**116.4585698**	**353.8461538**

A visual image of the Johnson S_B distribution can be given by the histogram of the simulated VTTS distribution for the four modes, as shown in Figure N. All simulations have been performed with 1000000 draws. The shape of the Johnson S_B distribution depends on its range. The simulated VTTS distributions for car, bus and rail sub-models are sharply U-shaped. Johnson et al. (1994: pg.37) highlight the possibility of U-shape.

Nevertheless, the interpretation of a U-shape VTTS distribution is *counterintuitive*, since it implies that a big share of the drivers (or passengers) is willing to pay almost nothing in order to save time. At the same time, a significant share of the market is willing to pay the *upper bound limit price*, but *no more* than that. The rest of the population is almost uniformly distributed in terms of WTP, with very small shares. Thus, the transition from low WTP to high WTP is not smooth in terms of market shares. For the plane sub-model the simulated distribution has a different shape, to which an exponential or Gamma curve might fit better. The share is monotonically decreasing in WTP. The convex shape suggests that the rate of decrease is falling as WTP gets higher.

Figure N: Simulated Johnson SB VTTS distributions with 1000000 draws



4.9 Johnson S_B with fixed upper bound

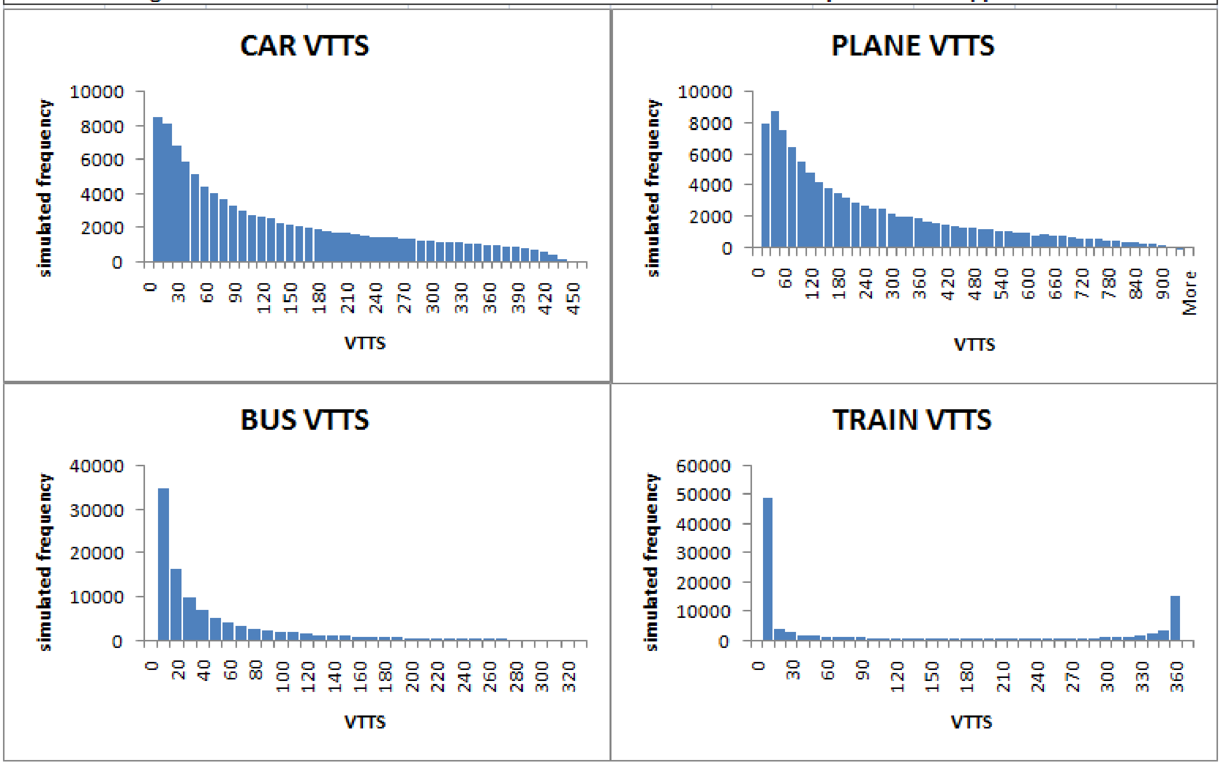
We now perform the following experiment. We fix the upper bound to a value that, with the existing estimates from the free upper bound model, accommodates 99.9% of WTP in the model with Normal mixing distribution. These are approximately 478.72 NOK for car, 900.06 NOK for plane, 305.74 NOK for bus and 350.63 NOK for train.

The sub-models are then re-estimated with their upper bounds fixed. Table 9c presents the results and Figure O the corresponding simulated VTTS distributions. In contrast to Model 4, all μ and σ estimates from Model 4’ are significant, with zero p-values.

Table 9c: Simulated VTTS and maximum WTP with fixed upper bound				
	Submodel 4'a:CAR	Submodel 4'b:PLANE	Submodel 4'c:BUS	Submodel 4'b:TRAIN
Simulated mean VTTS per hour	128.323	236.3909712	115.6636527	115.2032213
Simulated Std VTTS per hour	114.0227	216.702432	147.3388202	146.995096
Simulated VTTS upper bound per hour	436.2327204	932.5457569	356.25	356.25
Final log-likelihood	-3504.111	-1115.944	-2577.045	-3186.839
adjusted rho-square index	0.178	0.14	0.059	0.136

The simulated histograms are generated with 100000 draws. What is remarkable is the intuitive improvement in the shape of the VTTS distribution in the population for the modes car, plane and bus. The implied behavioral profile of the distributions in Figure O is undoubtedly more compatible with reality, assuming a monotonic decrease of density in VTTS, after the last has attained its peak. The implication is that a big share of the market is willing to pay small amounts, but people with high WTP also exist. In contrast to Model 4, in this model the transition is smooth, i.e. as the price of time increases beyond the price that represents the biggest market share, the market share declines.

Figure O: Simulated VTTS distributions with 0.999 normal distribution's percentile as upper bound.



We have thus managed to bound VTTS in some range which approximates the positive range of Normal, ruled out negative VTTS values and attained a Log-normal or exponential-like shape, which is intuitively-friendly. Unfortunately, in the last sub-model for rail, the VTTS distribution has retained its counterintuitive U-shape.

5. Socioeconomic segmentation of VTTS

Up to this point only attributes of the transport mode have been included as important factors in the cross-mode variance of VTTS. Individual characteristics however, can also play a key role. As Train (2002) points out, socio-economic variables can only enter the model in a way that generates differences in utility. One possibility is to specify interactions of the socio-economics with some attribute of the mode.

5.1 A model with income segmentation

The next model introduces income interaction with travel costs. The rationale behind this is that, based in declining marginal utility of income, the travel cost might have a different impact on people from various income segments. The systematic utility specification is:

$$V_{nL} = \alpha + \beta^{n}_{time} TT_L + \sum_{\lambda-\mu} \beta^{\lambda-\mu}_{\cos t} C_L I_{\lambda-\mu} + \beta_f F_L \quad \textbf{(Model 5)} \qquad (5.1)$$

$$V_{nR} = \qquad \beta^{n}_{time} TT_R + \sum_{\lambda-\mu} \beta^{\lambda-\mu}_{\cos t} C_R I_{\lambda-\mu} + \beta_f F_R$$

where the dummy variable $I_{\lambda-\mu}$ equals one if the respondent belongs to the income segment [λ,μ] and zero otherwise. This dummy coding allows the model to 'accept' differentiation of the price coefficient with respect to the respondent's income; there is a different cost coefficient for every income interval λ-μ. The selection of the income segments has been carried out after multiple estimations with various income segments. The selection criterion was the number of observations in an arbitrary interval and the significance of the estimates in those intervals. It must be remarked that all values (income, prices) are in 1994 NOK.

Table 10a presents the VTTS estimates for Model 5. The time coefficient is assumed to follow a Normal distribution; the assumption of normally distributed time coefficient has been maintained for reasons of convenience, despite the drawbacks that has demonstrated in Model 2, section 4.1.

Table 10a: VTTS Estimation results for Model 5				
	Sub-Model 5a: CAR	Sub-Model 5b: PLANE	Submodel 5c: BUS	Sub-Model 5d: TRAIN
Mean VTTS per min (income 0-100)	**1.739**	**2.772**	**0.5941**	**0.9492**
Std VTTS (income 0-100)	0.3386	0.4465	0.08349	0.09898
Robust t-test	5.137	6.21	7.116	9.59
Mean VTTS per min (income 100-200)	**1.784**	**2.888**	**0.8439**	**1.528**
Std VTTS (income 100-200)	0.1979	0.5416	0.1904	0.2223
Robust t-test	9.016	5.334	4.432	6.874
Mean VTTS per min (income 200-300)	**2.124**	**4.6**	**3.747**	**1.599**
Std VTTS (income 200-300)	0.2368	1.054	3.432	0.273
Robust t-test	8.969	4.363	***1.092	5.856
Mean VTTS per min (income over 300)	**3.019**	**11.46**	**1.464**	**2.736**
Std VTTS (income over 300)	0.6105	6.387	0.8594	0.9835
Robust t-test	4.945	**1.794	**1.703	2.783
Mean VTTS/hour (income 0-100)	**104.34**	**166.32**	**35.646**	**56.952**
Approximate 95% upper quantile limit VTTS/h	262.0314021	399.8304703	133.038649	165.2810318
Mean VTTS/hour (income 100-200)	**107.04**	**173.28**	**50.634**	**91.68**
Approximate 95% upper quantile limit VTTS/h	268.8348958	416.5653271	188.9861742	266.0965544
Mean VTTS/hour (income 200-300)	**127.44**	**276**	**224.82**	**95.94**
Approximate 95% upper quantile limit VTTS/h	320.0188804	663.4544099	839.0806906	278.3888957
Mean VTTS/hour (income over 300)	**181.14**	**687.6**	**87.84**	**164.16**
Approximate 95% upper quantile limit VTTS/h	454.8684715	1652.661722	327.7700266	476.4599116
Probability of negative VTTS (income 0-100)	0.138219487	0.120686423	0.273579968	0.19358757
Probability of negative VTTS (income 100-200)	0.138253512	0.120689455	0.27359306	0.193629772
Probability of negative VTTS (income 200-300)	0.138189469	0.12065914	0.273581078	0.193535997
Probability of negative VTTS (over 300)	0.13819097	0.120609134	0.27352317	0.193625083
*= not significant in 0.01 **=not significant in 0.05 ***=not significant in 0.1				

All mean VTTS estimates for the car and train sub-models are significant. For the plane and bus sub-models, mean VTTS for the highest income segment (300000+ NOK/year) is not significant at $\alpha = 0.05$. Also, mean VTTS is not significant at $\alpha = 0.10$ for the income segment 200000 to 300000 NOK/year. This is mainly due to lack of reasonable number of observations in these income segments. Table 10b shows the number of observations for each income segment.

Table 10b: Number of observations in income segments				
	Sub-Model 5a: CAR	Sub-Model 5b: PLANE	Submodel 5c: BUS	Sub-Model 5d: TRAIN
Nr.of observations (inc.0-100)	1017	665	2132	2708
Nr.of observations (inc.100-200)	2258	656	1007	1628
Nr.of observations (inc.200-300)	2231	557	476	1223
Nr.of observations (inc.300+)	1061	422	134	359
Total Nr. of Observations	6567	2300	3749	5918

Figure P provides the corresponding graphs for the VTTS estimates of Model 5. The increasing-in-income VTTS confirms that the marginal utility of time relative to the marginal utility of money tends to increase with respect to income. However, it is not possible to conclude about the rate of the increase (that is if the trend is linear, convex, concave or both with a saddle point) since the last income segment 300000+ NOK/year is open and some of the estimates are not significant.

Figure P: VTTS for various income segments

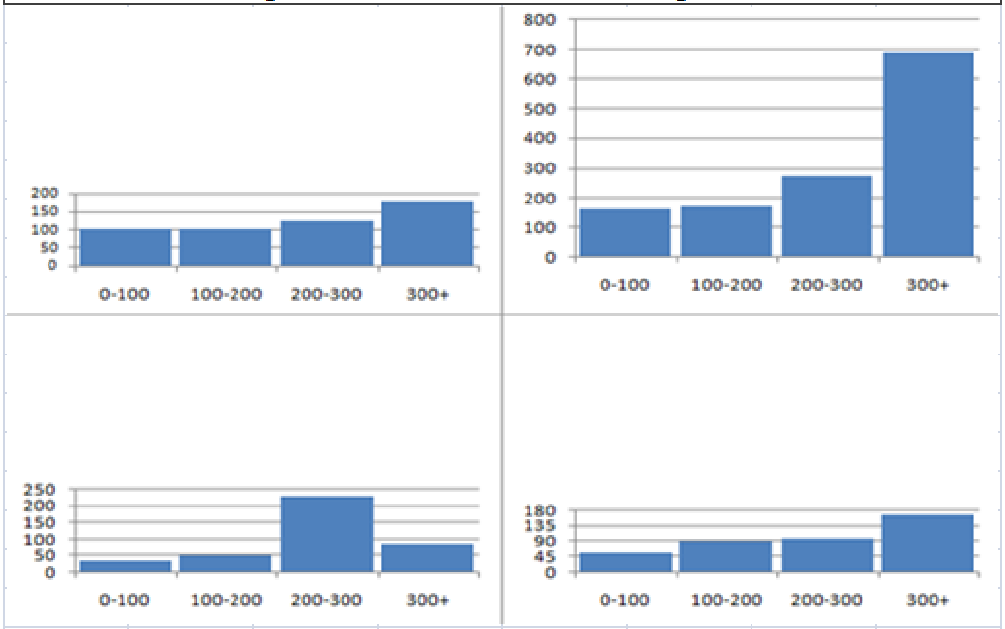


Table 10c provides the summary statistics for Model 5. In comparison to Model 2 which does not allow for income segmentation, Model 5 provides a better fit in all sub-models.

Table 10c: Summary statistics for Model 5				
	Sub-Model 5a: CAR	Sub-Model 5b: PLANE	Submodel 5c: BUS	Sub-Model 5d: TRAIN
Null Log-Likelihood	-4551.898	-1597.011	-2601.381	-4219.88
Final Log-Likelihood	-3381.657	-1292.734	-2342.017	-3427.902
Likelihood Ratio test	2340.589	608.544	518.729	1583.956
Adj. Rho-square index	0.255	0.186	0.097	0.186
*= not significant in 0.01 **=not significant in 0.05 ***=not significant in 0.1				

Finally, Table 10d presents a Likelihood Ratio test for the hypothesis of a uniform travel cost coefficient for all income segments (Model 2) against the alternative that at least one of the coefficients is different (Model 5). Model 2 constitutes a special case of Model 5 in which β's for every income segment are equal. The difference in the number of free parameters is three. The test is performed at $\alpha = 0.005$; the associated critical value of the chi-square distribution is 12.84. The test rejects all sub-models 2a-d in favor of 5a-d.

Table 10d: Generalized Likelihood Ratio test for the hypothesis of fixed cost coefficient (Model 2) versus the hypothesis of different segments (Model 5)				
	Car (sub-model 2a versus 5a)	Plane (sub-model 2b versus 5b)	Bus (sub-model 2c versus 5c)	Train (sub-model 2d versus 5d)
Log-likelihood under Model 2	-3410.891	-1329.414	-2507.08	-3462.56
Log-likelihood under Model 5	-3381.657	-1292.734	-2342.017	-3427.902
Test statistic	58.468	73.36	330.126	69.316
Chi-square critical value for α=0.005	12.84	12.84	12.84	12.84
Test result	Reject Model 2a	Reject Model 2b	Reject Model 2c	Reject Model 2d

5.2. A model with gender

This last model retains the specification of Model 5 but specifies a different distribution of the time coefficient for men and women. The general justification is that men and women might face different time constraints.

$$V_{nL} = \alpha + \beta_{time}^{nM} TT_L D_M + \beta_{time}^{nW} TT_L D_W + \sum_{\lambda-\mu} \beta_{\cos t}^{\lambda-\mu} C_L I_{\lambda-\mu} + \beta_{freq} F_L \quad \textbf{(Model 6)}$$

$$V_{nR} = \quad \beta_{time}^{nM} TT_R D_M + \beta_{time}^{nW} TT_R D_W + \sum_{\lambda-\mu} \beta_{\cos t}^{\lambda-\mu} C_R I_{\lambda-\mu} + \beta_{freq} F_R \qquad (5.2)$$

The new elements are the dummies D_M and D_W which equal 0 or 1 depending on the gender of the respondent (M stands for man and W for woman), and the two associated distributions for time coefficient. Table 11 below presents the VTTS estimates for the two genders and the four income segments. All estimations have been carried out with MSL estimation. The number of draws is 1000 for all sub-models, apart from train for which 500 draws were used (due to very slow convergence).

Table 11: VTTS Estimation results and summary statistics for Model 6				
	Submodel 6a: CAR	Sub-Model 6b: PLANE	Submodel 6c: BUS	Sub-Model 6d: TRAIN
Mean VTTS/hour (income 0-100) M	87.06	171.77	41.35	60.94
Mean VTTS/hour (income 0-100) W	106.56	148.94	32.7	59.06
Mean VTTS/hour (income 100-200) M	98.89	185.74	60.16	96.89
Mean VTTS/hour (income 100-200) W	121.05	161.05	47.58	93.91
Mean VTTS/hour (income 200-300) M	115.37	285.44	270	104
Mean VTTS/hour (income 200-300) W	141.22	247.5	213.53	100.8
Mean VTTS/hour (income over 300) M	189.2	718.89	97.45	202.07
Mean VTTS/hour (income over 300) W	231.6	623.33	77.07	195.85
Standard Deviation/hour (income 0-100) M	80.25	143.1	63.78	62.34
Standard Deviation/hour (income 0-100) W	99.2	122.12	57.84	82.27
Standard Deviation/hour (income 100-200) M	91.15	154.74	92.79	99.13
Standard Deviation/hour (income 100-200) W	112.68	132.06	84.14	130.81
Standard Deviation/hour (income 200-300) M	106.34	237.79	416.47	106.4
Standard Deviation/hour (income 200-300) W	131.46	202.94	377.65	140.4
Standard Deviation/hour (income over 300) M	174.4	598.89	150.32	206.74
Standard Deviation/hour (income over 300) W	215.6	511.11	136.31	272.8
Initial Log-Likelihood	-4252.458	-1303.81	-2601.381	-3587.037
Final Log-Likelihood	-3119.068	-1031.508	-2329.801	-2873.697
Likelihood Ratio test	2266.78	544.604	543.161	1426.679
Adj. Rho-square index	0.264	0.2	0.1	0.196
*= not significant in 0.01 **=not significant in 0.05 ***=not significant in 0.1				

Women from all income segments have higher VTTS than men in car. The opposite holds for the rest of the modes. A natural question that pops up in then: 'why is the pattern reversed from car to the rest of the modes and vice versa'? A hypothesis might be that long distance driving might be a relatively unpleasant experience for many women. Women car drivers may be seen as a different subpopulation than both men car drivers and women in the rest of the modes. The adjusted likelihood ratio index is higher than the corresponding of Model 6. The inclusion of gender as an explanatory has increased the fit of the model. Despite this, the likelihood ratio test has decreased in all modes except for bus.

While investigating the result tables from all models, some crucial questions emerge: Are these variations in VTTS due to *mode effects* (attributes of the mode such as perceived comfort and safety, departure frequency) or due to *user type effects* (self-selection)? Is it possible at all to distinguish the two effects? Can it be the case that a third type of effect is responsible for these variations? The last section aims to give an answer to these questions.

6. Sources of variation

6.1 Distinguishing the effects

Consider again Model 6. The results for men with annual income between 0 and 100000 NOK are:

	Submodel 6a: CAR	Sub-Model 6b: PLANE	Submodel 6c: BUS	Sub-Model 6d: TRAIN
	A1	A2	A3	A4
Mean VTTS/hour (income 0-100) M	**87.06**	**171.77**	**41.35**	**60.94**

Why does VTTS vary across modes? One explanation is *mode effects*. Under this hypothesis, *attributes of the mode* such as *comfort* and *safety* are responsible for these variations. People adjust their VTTS in each mode because they consider traveling with each mode as a different activity. Under this assumption however, we would expect bus VTTS to be higher than the rest of the modes, since bus is the least comfortable among these modes. Our estimates show the opposite direction. This is not a new phenomenon; 'It is common in VTT studies to find large differences in VTTS between transport modes in the opposite direction of what would be the consequence of differences in comfort' (Fosgerau et al., 2007).

Associated with the above observation is the hypothesis of *self selection*; under this, people migrate to transport modes that better suit their VTTS, which is *predetermined* by their socioeconomic status and is *not* activity related, i.e. mode related. Thus, the *user type effects* (the individual characteristics) are the only reason for VTTS variations. Self selection is a problem in econometrics and in social sciences because it 'blurs' the direction of causality; it is difficult to say whether the transport mode determines peoples VTTS or peoples' VTTS determines the choice of mode in the first place.

Is it possible at all to distinguish the two effects? Consider again low income (0-100000 NOK/year) men. Comparing car and plane VTTS we observe a change from 87.06 NOK/hour for car to 171.77 NOK/hour for plane. Part of this difference might be due to the *mode effects* and part due to *user type effects other than* income and gender*, since Model 6 controls for them*. Imagine now a situation where we would be able to control for *all* individual characteristics which may affect VTTS. That is if we could control for *age*, *family status*, *education* and every other individual aspect we would eventually be left with *user type effect free* estimates. This in turn implies that cells A1 to A4 would then *essentially refer to the same individual*. The remaining difference would purely be due to the *mode effects*. We would observe the exact same person in the four different modes.

The experimental design of the Norwegian VoT study allows for a similar possibility; the exact same respondent takes part in two SP experiments. The first experiment (SP1) measures the VTTS of an individual in the *reference mode* and the second (SP2) the VTTS of the *exact same person* in the chosen alternative mode for a trip similar to the reference trip. Thus, at least theoretically, *user type effects* in the two VTTS estimates are eliminated. A necessary prerequisite, however, is that the respondent *behaves as the same individual in the two* *experiments*. Therefore, we assume that answers in the two experiments are provided under identical psychological state. It is difficult however to say if this requirement is fulfilled. A respondent for example might *respond with different considerations to his/her income constraints in the two experiments*.

This leads to a third type of effect, namely *strategic responses*; 's*trategic behavior* can be an explanation for the observed differences between modes' (Fosgerau et al., 2007). If respondents behave strategically, they think outside the context of the experiment and believe that their responses may influence political decisions. Thus they 'detect' incentives against revealing their true WTP. Under the *strategic behavior* hypothesis, car drivers may have the tendency to overstate their VTTS, because they might think that there is no established mechanism to pay for reduced travel time. Or they could understate it, if they believe the result could encourage increased toll payments or fuel taxes. On the other hand, public transport passengers understate their VTTS because they might be afraid that expressing a higher willingness to pay for travel time savings will push for higher fares. *Strategic behavior* has *severe consequences on the reliability* of the VTTS estimates.

Following the specification of Model 2 (Normal mixing distribution), we now separate observations into *sixteen user groups*, as presented in Table 12. Each group contains users with identical reference *and* alternative mode. For example the first row refers to user group 1, the respondents with reference mode car and *chosen alternative* plane. Table 12 also shows the two mean VTTS estimates for *each* user group, one for the reference mode and one other for the alternative transport mode, i.e. the two experiment modes. The values in parentheses show the number of observations used in the estimation. *Mode effects* are then investigated by comparing the two mean VTTS estimates *within a user group*. *User type effects* are detected by *comparing mean VTTS estimates across user groups*.

This implies that *mode effects are checked horizontally* (in a given user group), while *user type effects are checked vertically* (in a given experiment mode). As an example, the difference between 181.9 NOK/h for car and 158.39 NOK/h for plane for user group 1 should be attributed to the *mode effect between car and plane.* On the other hand, the difference between 181.9 NOK/h, the mean VTTS *in car* for user group 1, and 117.84, the mean VTTS *in car* for user group 2, should be attributed to the *user type effect between user groups 1 and 2*.

Table 12: Mean VTTS for all user type groups and experiment modes										
USER TYPE GROUP			EXPERIMENT MODE							
			CAR		PLANE		BUS		TRAIN	
NR.GROUP	REFERENCE MODE	ALTERNATIVE MODE								
1	CAR	PLANE	181.9	(747)	158.39	(747)				
2	PLANE	CAR	117.84	(486)	*301.49	(486)				
3	CAR	BUS	92.08	(2500)			64.83	(2502)		
4	BUS	CAR	77.17	(1683)			52.25	(1692)		
5	CAR	TRAIN	96.59	(1296)					117.3	(1295)
6	TRAIN	CAR	240.29	(2519)					75.95	(2520)
7	PLANE	BUS			*175.19	(189)	67.83	(189)		
8	BUS	PLANE			***156.43	(405)	48.56	(405)		
9	PLANE	TRAIN			203.46	(720)			117.81	(719)
10	TRAIN	PLANE			51.08	(1395)			96.3	(1395)
11	BUS	TRAIN					**27.09	(1152)	51.72	(1152)
12	TRAIN	BUS					***12	(882)	52.41	(882)
13	CAR	NONE	124.43	(1412)						
14	PLANE	NONE			228.66	(252)				
15	BUS	NONE					46.71	(558)		
16	TRAIN	NONE							57.89	(522)
*= not significant in 0.01 **=not significant in 0.05 ***=not significant in 0.1										

6.2. User type effects

Generally, under *user type effects* we expect users of a relatively faster mode to project a higher VTTS in a slower alternative than the VTTS of the reference users of this slower alternative and vice versa. For example, we expect car drivers (reference mode car, alternative bus, user group 3) to have higher VTTS than bus passengers (reference mode bus, alternative car, user group 4) *in both bus and car*. The estimates (medium grey stripe) which are significant at $\alpha = 0.01$ show indeed higher VTTS for car drivers in both car *and* bus.

To test the statistical significance of the VTTS gap between *user type groups*, the following LR test, is performed. First, a model, in which all parameters are free is estimated for the *two user groups* in a *given experiment mode*.

(Test-model 1)

$$V_{nL} = \alpha + \beta_{time}^{n[G_1]EXP1} TT_L^{EXP1} D_{[G_1]} + \beta_{\cos t}^{[G_1]EXP1} C_L^{EXP1} D_{[G_1]} + \beta_{time}^{n[G_2]EXP1} TT_L^{EXP1}{}_L D_{[G_2]} + \beta_{\cos t}^{[G_2]EXP1} C_L^{EXP1} D_{[G_2]}$$

$$V_{nR} = \beta_{time}^{n[G_1]EXP1} TT_R^{EXP1} D_{[G_1]} + \beta_{\cos t}^{[G_1]EXP1} C_R^{EXP1} D_{[G_1]} + \beta_{time}^{n[G_2]EXP1} TT_R^{EXP1} D_{[G_2]} + \beta_{\cos t}^{[G_2]EXP1} C_R^{EXP1} D_{[G_2]}$$

(6.1)

Where *G* denotes the *user type group*, $D_{[Gi]}$ is a dummy that equals one if the respondent belongs to the *user type group i* and zero otherwise and *EXP* stands for the experiment mode. Note that *EXP* is kept fixed for both groups, i.e. we investigate the VTTS of two different groups, in the same experiment mode. We assume a Normal distribution with parameters μ and σ for time coefficients. The time coefficients are constant in the population. We estimate the model in 6.1.

Then, a restricted version of 6.1, where VTTS is constrained to be the same for the two user type groups is specified. That is, the Test-Model 1 is re-estimated under the non-linear equality constraint:

$$\frac{E(\beta_{time}^{[G_1]EXP_i})}{\beta_{\cos t}^{[G_1]EXP_i}} - \frac{E(\beta_{time}^{[G_2]EXP_i})}{\beta_{\cos t}^{[G_2]EXP_i}} = 0 \quad (6.2)$$

The final log-likelihood from the two test-models can be used in a LR test for the testing of hypotheses:

- H_0: $E(VTTS_{G_1}^{EXP_i}) = E(meanVTTS_{G_2}^{EXP_i}) \Leftrightarrow \frac{E(\beta_{time}^{[G_1]EXP_i})}{\beta_{\cos t}^{[G_1]EXP_i}} - \frac{E(\beta_{time}^{[G_2]EXP_i})}{\beta_{\cos t}^{[G_2]EXP_i}} = 0$
- H_1: $E(VTTS_{G_1}^{EXP_i}) \neq E(meanVTTS_{G_2}^{EXP_i}) \Leftrightarrow \frac{E(\beta_{time}^{[G_1]EXP_i})}{\beta_{\cos t}^{[G_1]EXP_i}} \neq \frac{E(\beta_{time}^{[G_2]EXP_i})}{\beta_{\cos t}^{[G_2]EXP_i}}$ (6.3)

For user groups 3 and 4 in experiment mode bus, the Likelihood Ratio test (Test 1 in Appendix Table A) on the above model *rejects* the null hypothesis of equal mean VTTS at $\alpha = 0.05$. The same pattern is observed in plane and train passengers (user groups 9 and 10); plane passengers display higher VTTS in both plane and train than train passengers. The difference is again statistically significant (Test 3 in Appendix Table A).

Also, plane-bus comparisons (user groups 7 and 8), suggest that plane passengers display a higher VTTS in both plane and bus (despite the estimates for VTTS measured in plane are not significant at $\alpha = 0.01$). Nevertheless, *this user type effect is not confirmed* by the corresponding LR test (Test 2 in Appendix Table A). In addition, the estimate for train passengers in bus is highly insignificant and does not allow us to identify *user type effects* between these groups (user groups 11 and 12).

On the other hand, plane passengers display lower VTTS than car drivers in car, where both estimates are significant (user type groups 1 and 2). We *cannot* identify *user type effects* between these groups.

6.3. Mode effects and strategic behavior

We now turn to *mode effects* and *strategic behavior*. Under *mode effects*, comfort and safety are expected to determine VTTS in the two experiment modes for a given *user type group*. This means that in an arbitrary *user type group*, VTTS is expected to be *lower* in the experiment mode that is perceived as relatively safer or more comfortable. The reader should bare in mind that safety and comfort might move in opposite directions; especially in the case of plane which might be perceived as more comfortable but less safe. Fosgerau et al. (2007) interpret results that point the opposite direction of comfort effects as products of *strategic behavior*.

To test the statistical significance of between experiment mode VTTS gaps in a given *user type group*, a similar test-model to Test-Model 1 is generated.

(Test-Model 2)

$$V_{nL} = \alpha + \beta_{time}^{n[EXP_i]G_1} TT_L^{EXP_i} D_{[EXP_i]} + \beta_{\cos t}^{[EXP_i]G_1} C_L^{EXP_i} D_{[EXP_i]} + \beta_{time}^{n[EXP_j]G_1} TT_L^{EXP_j}{}_L D_{[EXP_j]} + \beta_{\cos t}^{[EXP_j]G_1} C_L^{EXP_j} D_{[EXP_j]}$$

$$V_{nR} = \quad \beta_{time}^{n[EXP_i]G_1} TT_R^{EXP_i} D_{[EXP_i]} + \beta_{\cos t}^{[EXP_i]G_1} C_R^{EXP_i} D_{[EXP_i]} + \beta_{time}^{n[EXP_j]G_1} TT_R^{EXP_j}{}_L D_{[EXP_j]} + \beta_{\cos t}^{[EXP_j]G_1} C_R^{EXP_j} D_{[EXP_j]}$$

(6.4)

Again, G stands for the user type group, EXP_i and EXP_j for the experiment modes i and j and $D_{[EXPi]}$ is a dummy that equals one if the observation comes from the experiment mode i, zero otherwise. Note that, this time, G is fixed and EXP varies; all observations refer to the same *user type group* and we dummy code utility with respect to the experiment mode. The restricted version of 6.4 is the same model estimated under the non-linear equality constraint:

$$\frac{E(\beta_{time}^{[EXP_i]G_1})}{\beta_{\cos t}^{[EXP_i]G_1}} - \frac{E(\beta_{time}^{[EXP_j]G_1})}{\beta_{\cos t}^{[EXP_j]G_1}} = 0 \qquad (6.5)$$

As in the case of the *user type effects test*, estimating the final log-likelihood of the two versions allows for an LR test to be performed, in testing:

- H_0: $E(VTTS_{G_1}^{EXP_i}) = E(meanVTTS_{G_1}^{EXP_j}) \Leftrightarrow \frac{E(\beta_{time}^{[EXP_i]G_1})}{\beta_{\cos t}^{[EXP_i]G_1}} - \frac{E(\beta_{time}^{[EXP_j]G_1})}{\beta_{\cos t}^{[EXP_j]G_1}} = 0$
- H_1: $E(VTTS_{G_1}^{EXP_i}) = E(meanVTTS_{G_1}^{EXP_j}) \Leftrightarrow \frac{E(\beta_{time}^{[EXP_i]G_1})}{\beta_{\cos t}^{[EXP_i]G_1}} \neq \frac{E(\beta_{time}^{[EXP_j]G_1})}{\beta_{\cos t}^{[EXP_j]G_1}}$

Horizontal, within-user group comparisons suggest that the *evidence is mixed*. In car-plane (user group 1), *strategic behavior* can be the case in the first group, only if we assume that the result of mode effects is a higher VTTS in plane than in car, i.e. safety constitutes the major part of the mode effects, it overwhelms comfort effects. In other words user group 1 weights safety more than comfort, have actually higher VTTS in plane than in car but they understate it. This is of course a rather strong assumption.

A more sensible interpretation is that the effect in user group 1 is a *mode effect*; VTTS is lower in plane because people perceive it as both more comfortable and safer than car. The actual direction of mode effects for user group 1 is not clear; it is a group that has chosen plane as alternative, which might imply longer distance trips. In this case it may very well be the case that car is perceived as the less convenient mode. Therefore, the collision of mode and safety effects renders the direction of mode effects unclear.

For user group 2 (plane passengers) the difference can only be attributed to *mode effects* and is significant according to an LR test (Test 2, Appendix Table A).

Mixed evidence (two user groups, one with *mode effects* and one with hypothetical *strategic responses*) appears in car-train (user group 5) and train-car (user group 6). User group 5 expresses a higher VTTS in train than in car, which can be interpreted as a *mode (comfort) effect.* People just perceive train as less comfortable mode relative to car. Unlike user group 1, this effect is much clearer. Despite this, the observed *mode effect* in this group is rejected by a LR test with $\alpha = 0.01$ (Appendix Table B, test 5).

On the other hand the 'strategic difference' in user group 6 (people probably understate VTTS in train) is highly statistically significant and cannot be rejected at any level of significance (Appendix Table B, test 7).

Another situation is the one encountered in the pair plane-train (user group 9) and train-plane (user group 10). In this case *both experiment modes are public*. User group 9 expresses a higher VTTS in plane than in train. Since plane is generally more comfortable, this could be interpreted as a *safety effect*. User group 10 displays the opposite, which might be interpreted as a *comfort effect*.

In the case of user groups 9 and 10 strategic responses cannot be identified even if they exist, since the perception of the respondent relative to the *price enforcement mechanisms* relative to the two experiment modes is unknown. It might be the case that the respondent assumes identical mechanisms, since both modes are public transport. Actually, in absence of additional information about *price enforcement mechanisms* we cannot identify any *strategic effects* between public transport modes.

Strategic behavior dominates in car-bus (user group 3) and bus-car (user group 4); both groups express significantly higher WTP in car than in bus. The difference in expressed VTTS for user group 3 in car and bus is very strong (Test 4 in Appendix Table B). On the other hand the 'strategic responses' of user group 4 in bus and car are not significant in $\alpha = 0.01$ (Test 6 in Appendix Table B).

Mode effects seem to dominate in plane-bus, bus-plane (user groups 7 and 8). Both groups express higher WTP in plane, which can be interpreted as a safety effect. This interpretation however can be only tentative, given that the VTTS estimates of both user groups in plane are not significant.

Mode effects are also present between the two public transport modes, bus and train. The estimates for train seem to be higher (the values for bus are not based on significant estimates) in both train-bus (user group 12) and bus-train (user group 11). This is again tentative, since both estimates in experiment mode bus are insignificant. If this is the case, however, and in absence of additional information on different *perceptions of the respondent on the price enforcement mechanisms* associated with the two modes , the remaining difference can be attributed to mode effects, i.e. that bus is actually perceived as more comfortable than the train.

Table 13: A joint Likelihood Ratio test						
NR.GROUP		USER TYPE GROUP	EXPERIMENT MODE			
			CAR	PLANE	BUS	TRAIN
15	BUS	NONE			46.71	
4	BUS	CAR	77.17		52.25	
8	BUS	PLANE			48.56	
11	BUS	TRAIN				51.72

Finally, if we merge user groups 4,8,11 and 15, that is all user groups with reference mode bus, we can perform a joint LR test as shown in the Appendix Table C to test the null hypothesis that all VTTS estimates of Table 13 are equal against the alternative, that at least one mean VTTS differs. The test does not reject the null hypothesis in $\alpha = 0.01$.

7. Concluding remarks and future challenges

We now summarize the most important findings, concerning the causes of VTTS variation. The most solid finding is the vulnerability of VTTS estimates to the model used (*cross model variations*).

Figure Q: Cross-mode(horizontal) and cross-model (vertical) mean VTTS variations

MODE MODEL	CAR	PLANE	BUS	RAIL
LOGIT	88.4 NOK	178.5 NOK	35.4 NOK	47.9 NOK
MIXED LOGIT NORMAL	123.8 NOK	242.6 NOK	44.7 NOK	75.5 NOK
MIXED LOGIT LOGNORMAL	166.4 NOK	305 NOK	40.3 NOK	585.5 NOK
MIXED LOGIT JOHNSON SB	118.7 NOK	236.4 NOK	40.2 NOK	108 NOK

Figure Q summarizes the mean VTTS estimates for all models (vertically) and modes (horizontally). *The extent of the cross-model variation is not irrelevant to mode*. For instance, estimates of VTTS seem to be more robust for bus than for the rest of the modes. A possible explanation is that bus passengers are a more homogeneous group than the rest that is, data on bus might be more informative.

Next, we summarize the main conclusions from experimenting with logit and random coefficient models with different mixing distributions. The lowest estimates were produced from the pure logit model (Model 1, section 4.1). We highlighted the major drawbacks of logit and rationalized the use of models with random coefficients. Using a Normal mixing distribution for the random time coefficient yielded higher mean VTTS and also some non negligible probability of getting negative VTTS (Model 2, section 4.5). The use of Lognormal, despite solving the problem of negative VTTS, inflated all mean VTTS estimates and produced an obscurely high mean VTTS for the case of rail (Model 3, section 4.6). Perhaps the most optimistic result is the intuitive-friendly shape of the Johnson S_B VTTS distribution with both bounds fixed, in Model 4b (section 4.9). This result was obtained after one attempt with free upper bound which, despite yielding sensible mean VTTS estimates, provided insignificant parameter estimates and a counterintuitive shape for the VTTS distribution (Model 4a, section 4.8). Despite this, Normal distribution was adopted for the estimations of Chapters 5 and 6, mainly for convenience since the moments of a Johnson S_B distribution must be approximated by simulation. Further use of Johnson S_B is left as a future challenge.

Perhaps, some possibilities for estimation were neglected, mainly *non parametric methods* and alternative specifications with different mixing distributions. It is possible that a discrete VTTS distribution with mass points and their frequencies treated as parameters (Train, 2008) could be more flexible in approximating the 'real' VTTS distribution. Also, the performance of a practical test for the justification of the mixing distribution, based on Fosgerau and Bierlaire (2007), can provide a further development of this study in the future.

We then focused on *cross-mode VTTS* differences derived from a fixed hybrid model (mixed logit with Normal mixing distribution). We discussed an intuitive method for separating the two main causes of cross-mode VTTS variations, namely *mode* and *user type effects* in section 6.1. We also referred to a third theoretical possibility, *strategic behavior*. The evidence concerning *mode* and *user type effects* was mixed. *User type effects* were confirmed in two cases; for plane passengers in train, where they transfer their high VTTS, and for car drivers in bus, where they carry a higher VTTS than bus passengers. A third user type effect for plane passengers in bus was rejected by a LR test despite the observed differences in VTTS.

Mode effects emerge in car drivers with rail alternative, but the LR test 5 (Appendix Table B) cannot reject the null hypothesis of equal VTTS (no mode effects). Despite this, we have managed to confirm *mode effects* in the case of user group 2; plane passengers are observed to have a significantly lower VTTS in car, which might be a mode (possibly safety-related) effect. It is also perfectly possible that the VTTS differences between the two experiment modes plane and train in user groups 9 and 10 are due to *mode effects*.

Strategic behavior is evident in some groups and mixes up the picture concerning the previous two types of effects. *User type effects* that were previously confirmed for car drivers and bus passengers are *blurred* by the assumption that car drivers (Table 12, *user type group* 3) understate their VTTS in bus and overstate their VTTS in car; if the estimates of user group 3 are strategically biased we can't be sure that vertical differences between user groups 3 and 4 represent *user type effects*. The strategic effect for the user group 3 is very strong (Test 4, Appendix Table B). *Strategic behavior* might also prevent *user type effects* from being identified between car drivers and train passengers (Table 12, user groups 5 and 6), since the strategic effect for the user group 6 is strong (Test 7, Appendix Table B).

The way respondent '*differentiates*' between the experiment in the reference and alternative mode and the *ability of the respondent to perform strategic responses* under given experiment conditions (experiment duration, place of interview) and personal characteristics (*education*, age) is however *questionable* and constitutes a challenge for additional research. For this reason, all results that refer to *strategic behavior*, despite statistically robust, have limited theoretical support.

Therefore, the general conclusion is that cross-mode differences in VTTS are mainly explained by a specific effect is somewhat *risky* for the Norwegian case. *User type effects* certainly exist, but *mode effects* are also present. If we accept that strategic responses can exist at all, they are significant in at least two user groups and constitute a threat to the validity of the VTTS estimates. It is therefore essential for the experimental design and sampling process of the forthcoming VoT studies to develop tools in order to reduce/eliminate this threat.

Another future challenge is the development of more sophisticated specifications which could give more analytic VTTS estimates, controlled for a wider range of user type effects. In this study we have performed VTTS segmentations with respect to income and gender (Chapter 5). A more sophisticated model would incorporate many others (e.g. age, location). This will increase our understanding on the role of socioeconomic background on VTTS. Unfortunately this process is not irrelevant to the stage of sampling. Elegant models with multiple segments are associated with the fact that some groups of population will not be 'covered' by the sample; in other words, there will not be a reasonable number of observations in order to guarantee significant VTTS estimates for these groups. The *trade off* between the ability to control for *user type effects* and the possibility to get significant estimates for small user groups is setting limits to researcher's ambitions. Nevertheless, the extent of this trade off can be controlled in the sampling stage, by ensuring that a sufficient number of observations 'covers' the characteristics of the various user groups. This of course, raises the cost of the survey.

Appendix A: Likelihood Ratio tests

This is a synopsis of the LR tests used in section 4.11 for checking if the VTTS estimates of user groups and transport modes differ significantly.

Appendix Table A: LR tests for user type effects

	TEST 1	TEST 2	TEST 3
USER GROUP 1	[CAR-BUS-bus]	[PLANE-BUS-bus]	[PLANE-TRAIN-train]
USER GROUP 2	[BUS-CAR-bus]	[BUS-PLANE-bus]	[TRAIN-PLANE-train]
NULL HYPOTHESIS (H0)	Equal Mean VTTS	Equal Mean VTTS	Equal Mean VTTS
ALTERNATIVE HYPOTHESIS (H1)	Different Mean VTTS	Different Mean VTTS	Different Mean VTTS
L.LIKELIHOOD UNDER H0 (Restricted Model)	-2668.45	-322.194	-1086.114
L.LIKELIHOOD UNDER H1 (Free Model)	-2665.733	-321.249	-1063.762
LR TEST STATISTIC	5.434	1.89	44.704
DEGREES OF FREEDOM	1	1	1
CRITICAL VALUE χ-square FOR α = 0.05	3.84	3.84	3.84
DECISION FOR α = 0.05	REJECT H0	ACCEPT H0	REJECT H0
Notation for user groups: [REFERENCE MODE-ALTERNATIVE MODE-experiment mode]			

Appendix Table B: LR tests for mode effects and strategic responses

	TEST 4	TEST 5	TEST 6	TEST 7
USER GROUP	[CAR-BUS]	[CAR-TRAIN]	[BUS-CAR]	[TRAIN-CAR]
EXPERIMENT MODE 1	CAR	CAR	BUS	TRAIN
EXPERIMENT MODE 2	BUS	TRAIN	CAR	CAR
NULL HYPOTHESIS (H0)	VTTS(mode 1)=VTTS(mode 2)	VTTS(mode 1)=VTTS(mode 2)	VTTS(mode 1)=VTTS(mode 2)	VTTS(mode 1)=VTTS(mode 2)
ALTERNATIVE HYPOTHESIS (H1)	VTTS(mode 1)≠VTTS(mode 2)	VTTS(mode 1)≠VTTS(mode 2)	VTTS(mode 1)≠VTTS(mode 2)	VTTS(mode 1)≠VTTS(mode 2)
L.LIKELIHOOD UNDER H0 (Restricted Model)	-2824.958	-1476.935	-2021.93	-2711.51
L.LIKELIHOOD UNDER H1 (Free Model)	-2769.98	-1475.484	-2019.287	-2678.88
LR TEST STATISTIC	109.956	2.902	5.286	65.26
DEGREES OF FREEDOM	1	1	1	1
CRITICAL VALUE χ-square FOR α = 0.01	6.63	6.63	6.63	6.63
DECISION FOR α = 0.01	REJECT H0	ACCEPT H0	ACCEPT H0	REJECT H0
Notation for user groups: [REFERENCE MODE-ALTERNATIVE MODE]				

Appendix Table C: Joint LR test BUS

USER GROUP 1	[BUS-NONE][bus]
USER GROUP 2	[BUS-CAR][bus]
USER GROUP 3	[BUS-PLANE][bus]
USER GROUP 4	[BUS-TRAIN][train]
USER GROUP 5	[BUS-CAR][car]
NULL HYPOTHESIS (H0)	Uniform mean VTTS
ALTERNATIVE HYPOTHESIS (H1)	At least one VTTS differs
L.LIKELIHOOD UNDER H0 (Restricted Model)	-3294.485
L.LIKELIHOOD UNDER H1 (Free Model)	-3288.984
LR TEST STATISTIC	11.002
DEGREES OF FREEDOM	4
CRITICAL VALUE χ-square FOR α = 0.01	13.28
DECISION FOR α = 0.01	ACCEPT H0
Notation: [REFERENCE MODE-ALTERNATIVE MODE][experiment mode]	

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