The Value of Time over Time

A Further Investigation on the Norwegian Value of Time Study

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Abstract

An important issue in the field of transport economics is the discrepancy between cross-sectional and longitudinal income elasticity of the Value of Travel Time Savings (VTTS). Policy makers and transport planners use the income elasticity of VTTS to calculate future VTTS. A major part of benefits of transport investments is due to travel time savings. Different values used for income elasticity of VTTS leads to different calculations of future benefits, and could affect the result of a cost-benefit analysis. In The Norwegian Value of Time Study income elasticity of VTTS was estimated to be about 0.5. The comparison of estimated VTTS based on 1996 data and 2009 data suggests an income elasticity of about 1.0 (Ramjerdi et al., 1997; Ramjerdi et al., 2010).

The main focus on this thesis is to explore possible explanations for the divergence of cross-sectional and longitudinal income elasticity of VTTS. An econometric model is formulated to estimate income elasticity of VTTS based on data from the Norwegian Value of Time Study. The cross-sectional income elasticity of VTTS is estimated for different segments of data. It is found that cross-sectional income elasticity of VTTS most likely is an increasing function of income. There is also evidence indicating that cross-sectional income elasticity increases with age. Both of these factors could cause cross-sectional and longitudinal income elasticity of VTTS to converge over time. It is suggested that further studies on the subject are needed in order to identify possible solutions to the problem at hand.

Preface

I would like to thank my supervisor, Farideh Ramjerdi at the Institute of Transport Economics, for introducing me to the field of transport economics and providing me with excellent support throughout the writing process. Without her guidance and advice the completion of this thesis would not have been possible.

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Any errors or inaccuracies in this thesis are my responsibility alone.

Table of Content

1 Introduction

This thesis is concerned with how the Value of Travel Time Savings (VTTS) evolves over time. It is important to know the VTTS because it often is the main component of benefit streams in a cost-benefit analysis for transport investment (Fosgerau, 2005). Mackie, Jara-Díaz and Fowkes (2001) suggest that VTTS accounts for about 80% of the monetized benefits within the cost-benefit analysis of major road schemes in the UK. A transport investment project usually takes place over a long period of time. Therefore, it is also important to be able to predict what the VTTS will be when the project is finished and during the lifetime of the project in order to obtain a correct estimate for the benefits.

It is possible to predict future VTTS by utilizing the income elasticity of current VTTS estimated from cross-sectional data. By combining current VTTS, the cross-sectional income elasticity and expected income growth it is possible to predict how VTTS will evolve over time. Another possibility is to calculate the longitudinal income elasticity of VTTS. This is done by comparing VTTS and income for a population, in studies conducted at different points in time. As it turns out, these two types of income elasticities do not generally coincide. Longitudinal income elasticity tends to be higher than cross-sectional income elasticity (Wardman, 2009). This means that using the longitudinal income elasticity will predict a future VTTS that is higher than by using the cross-sectional income elasticity.

The goal of this thesis is to identify possible reasons for the discrepancy between cross-sectional and longitudinal income elasticity of VTTS. By formulating an econometric model based on data collected for the Norwegian Value of Time Study (Ramjerdi, 2010), I investigate how cross-sectional income elasticity varies when data is segmented and different explanatory variables are used.

This thesis will proceed as follows. Chapter 2 introduces the theoretical framework on how time can be assigned a value when used in different activities, and how this is related to VTTS. Chapter 3 explains the econometric toolkit that is available for VTTS estimation. Further, Chapter 4 presents empirical evidence on VTTS and income elasticities. Chapter 5 shows how data for the Norwegian Value of Time Study was collected. Chapter 6 derives the econometric model formulation used for estimation. Chapter 7 gives the results of estimation. Finally, Chapter 8 concludes the thesis.

2 Theoretical Framework

2.1 The Value of Time

Acknowledging that time is a vital factor when a consumer face a consumption decision is essential for understanding how to estimate the Value of Travel Time Savings (VTTS). Individuals spend their time consuming market goods, and by allowing time to enter the utility function, it is possible to estimate the value of time in different usages. Several economists have developed frameworks for consumer behaviour in which time plays an important role. In his study on female labour supply Mincer (1962) claims that it is difficult to separate time spent at work from time spent for leisure. This is due to the fact that a lot of non-work activities defined as leisure might actually include the production of goods and services at home. He recognizes the need for time usage to be divided into a greater number of categories than just work and leisure. Lancaster (1966) states that individuals do not derive utility from the direct consumption of market goods. Rather, it is from the characteristics of market goods that individuals obtain utility. He defines a consumption activity as a relationship between the market good consumed and the level of activity associated with each market good. The different consumption activities produce characteristics of the market goods. In the following, I will consider two seminal papers by Becker (1965) and DeSerpa (1971) on how time can be valued in different consumption activities. This can be applied to the valuation of travel time savings by claiming that travel can be seen as a consumption activity. Ramjerdi (1993) gives an overview on other important contributions on how to estimate the value of travel time savings.

2.2 Becker

Becker (1965) was one of the first economists to introduce the time dimension to the utility function of the consumer. He emphasize that the value of time is an important factor to consider when households makes decisions about non-work activities. Consumption is not only the purchase of market goods, but also the time a consumer has to allocate in order to consume the market goods. In relation to this, he defines commodities as a function of both market goods and time. A commodity could for example be travelling by bus. In this case the market good would be the purchase of a bus ticket. However, the consumer would also have to spend time consuming the market good by riding the bus. Commodity i can be written as in equation (2.1).

$$Z_i = f_i(x_i, T_i) \tag{2.1}$$

f_i is a function of a vector of market goods x_i, and a vector of time inputs T_i, needed to produce commodity i. In this formulation households are the producers of commodities. The households want to consume these commodities so that they maximize their utility function given by equation (2.2).

$$U = U(Z_1, \dots Z_m) \equiv U(f_1, \dots f_m) \equiv U(x_1, \dots x_m;\ T_1, \dots T_m) \tag{2.2}$$

The subscript m denotes the number of commodities that are being produced by the consumer. Corresponding to this utility function are constraints on both income and time given as

$$\sum_1^m p_i x_i = I = V + T_w \bar{w} \tag{2.3}$$

$$\sum_1^m T_i = T_c = T - T_w \tag{2.4}$$

In the first of these constraints I is total income, T_w is time spent working and $\bar{w}$ is wage. Thus, $T_w \bar{w}$ is earned income. V is income from other sources. In the second constraint T is defined as total time available and T_c is total time spent for consumption.

Becker recognizes that these two constraints are not independent by utilizing the fact that T_w enters in both expressions. By substituting for T_w, one of the constraints can actually be removed. We end up with the following budget constraint:

$$\sum_1^m p_i x_i + \sum_1^m T_i \bar{w} = V + T\bar{w} \tag{2.5}$$

Furthermore, it is possible to write x_i and T_i as functions of Z_i.

$$x_i = b_i Z_i \tag{2.6}$$

$$T_i = t_i Z_i \tag{2.7}$$

In equation (2.6) b_i is the amount of market goods used per unit of Z_i, and in equation (2.7) t_i is the amount of time spent per unit of Z_i. Inserting these expressions for x_i and T_i in the budget constraint yields the following Lagrange optimization problem:

$$L = U(Z_1, \dots Z_m) - \lambda\left(\left[\sum_1^m p_i b_i + \sum_1^m t_i \, \overline{w}\right] Z_i - V - T\overline{w}\right) \tag{2.8}$$

We find the first order condition by differentiating with respect to Z_i.

$$\frac{\partial U}{\partial Z_i} = \lambda\left[\sum_1^m p_i b_i + \sum_1^m t_i \, \overline{w}\right] \tag{2.9}$$

It is convenient to rewrite the expression within the brackets so that we end up with the equation (2.10).

$$\pi_i = \sum_1^m p_i b_i + \sum_1^m t_i \, \overline{w} \tag{2.10}$$

By introducing the time dimension to the optimization problem Becker derived that the full price per unit of commodity i is not just the price of the market good itself, but also the value of time used to consume the market good. Thus, it is possible to divide the price of a commodity into a direct part consisting of the market goods used, and an indirect part consisting of the time used. The full price of commodity i can then be written as π_i, which incorporates the price of time into consumption decisions. The Lagrange-multiplier λ can be interpreted as the marginal utility of money income. In Becker's model, the value of time is equal to the consumer's foregone wages. This means that VTTS should be set equal to the wage rate.

2.3 DeSerpa

Another approach is to treat time and consumption goods as two separate arguments in the utility function. DeSerpa (1971) defines a set of commodity bundles as

$$X = (X_1, \dots, X_n, T_1, \dots, T_n) \tag{2.11}$$

X_i represents the quantity consumed of consumption good i, while T_i is the amount of time allocated to good i. Corresponding to this is the utility function of the consumer as shown in equation (2.12).

$$U = U(X) \tag{2.12}$$

The consumer wants to maximize her utility function subject to the constraints on money income and time given by equation (2.13) and (2.14).

$$Y = \sum_{i=1}^{n} P_i X_i \tag{2.13}$$

$$T^0 = \sum_{i=1}^{n} T_i \tag{2.14}$$

In the first constraint, Y equals money income and $P_i X_i$ is the amount of money spent on good i. This represents the classic budget constraint saying that the full money income is spent on a bundle of consumer goods. The second constraint is concerned with the allocation of time consuming different goods. The total amount of time available to the consumer is T^0, and T_i is the time allocated to the consumption of good i. But in contrast to Becker (1965), these two constraints are not dependent of each other.

In addition to these two constraints is a constraint stating how much time is actually being spent on each consumption activity. This constraint is given by equation (2.15).

$$T_i \geq a_i X_i \tag{2.15}$$

The parameter a_i can be seen as consumption technology defining the minimum requirement of time to be spent consuming good i. The reasoning behind this constraint is that some consumption activities can be seen as burdensome, while other consumption activities might be seen as pleasurable. For the burdensome activities the constraint will be binding as the consumer do not want to spend more time on this activity than necessary. For the pleasurable activities the constraint will not be binding as it is possible that the consumer want to spend more time on these activities than the required minimum.

By combining all three constraints, the optimization problem of the consumer can be written as a Lagrange function.

$$L = U(X_1, \dots, X_n, T_1, \dots, T_n) + \lambda\left(Y - \sum_{i=1}^{n} P_i\, X_i\right) + \mu(T^0 - \sum_{i=1}^{n} T_i) + \sum_{i=1}^{n} K_i\,(T_i - a_i X_i) \qquad (2.16)$$

The parameters λ and μ are strictly positive Lagrange-multipliers representing the marginal utility of money and time. K_i is the Lagrange-multiplier related to each consumption activity, and can be seen as the marginal utility of saving time on activity i. Due to that fact that this constraint may be non-binding, the value of K_i is either zero or positive. The first order conditions to this problem are given by equation (2.17) and (2.18).

$$\frac{\partial U}{\partial X_i} = \lambda P_i + K_i a_i \qquad (2.17)$$

$$\frac{\partial U}{\partial T_i} = \mu - K_i \qquad (2.18)$$

Furthermore, the last constraint yields

$$K_i(T_i - a_i X_i) = 0 \qquad (2.19)$$

This means that either K_i or $T_i - a_i X_i$ is equal to zero, depending on whether the constraint binds or not for consumption activity i.

It is convenient to divide equation (2.18) by λ.

$$\frac{\frac{\partial U}{\partial T_i}}{\lambda} = \frac{\mu}{\lambda} - \frac{K_i}{\lambda} \qquad (2.20)$$

μ/λ is the marginal rate of substitution between time and money. This can be interpreted as the resource value of time, which is equal to the wage rate. Further, the ratio $\frac{\partial U}{\partial T_i}/\lambda$ is the marginal rate of substitution of T_i for money. This represents the value of time as a commodity (DeSerpa, 1971, p.833). The value of time as a commodity and the value of time as a resource are equal only if an individual spends more time on that activity than the minimum requirement. In this case, equation (2.15) does not bind. An example of this could be a pleasurable activity such as leisure. The value of leisure is then equal to the resource value of time, μ/λ.

DeSerpa states that the algebraic differences between the value of time as a resource and the value of time as a commodity determine the value of saving time from that activity. Thus, the expression in equation (2.20) can be rearranged to give equation (2.21).

$$Value\ of\ Saving\ Time\ Consuming\ X_i = \frac{\mu}{\lambda} - \frac{\frac{\partial U}{\partial T_i}}{\lambda} = \frac{K_i}{\lambda} \tag{2.21}$$

It’s readily seen that the value of saving time in leisure activities is equal to zero. For travelling, the constraint in (2.15) will bind since it is a burdensome activity. This will cause a discrepancy between the value of time as a resource and the value of time as a commodity. The difference between these two values will constitute VTTS. DeSerpa’s model emphasize that the value of time will be different for each consumption activity. This is in contrast with Becker (1965) who simply equalled the value of time to the foregone wages for each consumption activity.

The theoretical framework provided by Becker (1965), DeSerpa (1971), and other economists, is of great importance for the estimation of VTTS. However, theoretical principles alone are not enough. Hensher (2007) emphasize that determining VTTS is just as much a question of empirical study. It cannot be derived solely from economic theory. Econometric methods have been developed that makes it possible to estimate VTTS empirically. A group of models called discrete choice models are important in this respect.

3 Discrete Choice Models

3.1 The Behavioural Process

According to Train (2009), the goal of discrete choice models is to understand the behavioural process that leads to an agent's choice, with the agent in this case being an individual. A choice set is defined as all the different alternatives an individual can choose from. The alternatives faced by an individual must be mutually exclusive, meaning that choosing one alternative implies no other alternative can be chosen. In addition to this, the alternatives also have to be exhaustive. All alternatives available to an individual must be included. Finally, the number of alternatives must be finite.

It is possible to describe an individual's choice as a function of observable and unobservable factors describing that particular person. Following the notation of Train (2009), this can be written as in equation (3.1).

$$y = h(x, \varepsilon) \tag{3.1}$$

x are the observable factors and ε is the error term that accounts for the unobserved factors. The unobserved factors could be unobserved attributes, unobserved taste variation or measurement errors.

Equation (3.1) is referred to as the behavioural process. It is common to put $y = 1$ if the alternative was chosen, and $y = 0$ if it was not chosen. The factors ε are unobservable to the researcher, but known to the individual. This means that an individual's choice cannot be predicted exactly. It is, however, possible to calculate probabilities related to each alternative in a choice set. The probability that an individual chooses a specific alternative is the probability that the unobserved factors are such that the behavioural process results in that outcome (Train, 2009, p.3). Equation (3.2) shows another way of stating this.

$$P(y|x) = Prob(\varepsilon \ s.t. \ h(x, \varepsilon) = y) \tag{3.2}$$

There are different ways of specifying $h(x, \varepsilon)$ giving rise to different discrete choice models. Crucial here is the assumption about the error term ε. Assuming that ε is distributed logistically over the population yields the logit model. If ε is assumed to be normally distributed this results in the probit model.

3.1.1 Representative Utility

It is common to assign a representative utility function to each alternative available to an individual in order to be able to calculate choice probabilities. The representative utility function of alternative i for individual n is given by equation (3.3).

$$V_{ni} = \beta x_n \tag{3.3}$$

β is a vector of parameters and x_n is the corresponding vector of individual-specific variables. These variables could be the cost and other characteristics of the alternative and the socio-economic attributes of each individual (Jara-Díaz, 2000, p.309). By using alternative specific constants it is possible to capture the effects of factors that are not included in the model.

3.1.2 Adding the Error Term

Representative utility only account for the observable part of utility. Only by knowing the unobservable error term ε_{ni} one can infer what alternative will be chosen. The actual utility obtained by individual n choosing alternative i is given by equation (3.4).

$$U_{ni} = V_{ni} + \varepsilon_{ni} \tag{3.4}$$

Because ε_{ni} is unknown to the researcher, it is only possible to make probability statements about what alternative is going to be chosen by an individual. The error term can be seen as the unmeasured characteristics of an individual relating to an alternative.

It is only the difference in utility between the alternatives that matters. The absolute level of utility is irrelevant to both the decision maker's behaviour and the researcher's model (Train, 2009, p.19). Furthermore, scaling the utilities of different alternatives by some constant does not change the choice probabilities. It is common to scale the utility such that the variance of the error terms is normalized (Train, 2009: p.23).

Following Train (2009), the probability of individual n choosing alternative i can be written as in equation (3.5) – (3.7).

$$P_{ni} = Prob\left(U_{ni} > U_{nj} \;\forall\, j \neq i\right) \tag{3.5}$$

$$P_{ni} = Prob\left(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj} \;\forall\, j \neq i\right) \tag{3.6}$$

$$P_{ni} = Prob(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \;\forall\, j \neq i) \tag{3.7}$$

P_{ni} can be interpreted as the probability of any person with the same amount of observed utility V_{ni} actually choosing alternative i. The probability of individual n choosing alternative i is dependent not only on the observable factors, but also on the sizes of the unobservable error terms associated with each individual for each alternative. Equation (3.8) shows how the joint distribution of the error terms for individual n can be written.

$$\bar{\varepsilon}_n = (\varepsilon_{n1}, \dots, \varepsilon_{nJ}) = f(\varepsilon_n) \tag{3.8}$$

$\bar{\varepsilon}_n$ is a vector of error terms for an individual n, and $f(\varepsilon_n)$ is the distribution of error terms for that particular individual.

Section 3.2 continues by describing the logit model. With the introduction of simulation techniques the logit model can be transformed into the more advanced mixed logit model. This is the topic of Section 3.3. Both these types of models are highly popular in the field of VTTS estimation.

3.2 The Logit Model

3.2.1 Distribution of the Error Terms

The logit formula for choice probabilities imply that the error terms ε_{nj} for different alternatives are independently, identically distributed extreme value (Train, 2009, p.34). Independence of the error terms means that the researcher cannot predict the values of the other error terms by knowing the value of one of the error terms. In other words, the unobserved portions of utility for different alternatives are not correlated. If the researcher has specified the representative utility functions in a proper manner, such that the unobserved parts of utility are truly independent, the logit model is appropriate. It is then possible to write the density of the unobserved part of utility as in equation (3.9).

$$f(\varepsilon_{nj}) = e^{-\varepsilon_{nj}} e^{-e^{-\varepsilon_{nj}}} \tag{3.9}$$

The corresponding cumulative distribution function is given in equation (3.10)

$$F(\varepsilon_{nj}) = e^{-e^{-\varepsilon_{nj}}} \tag{3.10}$$

The variance of this distribution is $\frac{\pi^2}{6}$. By assuming that the variance is $\frac{\pi^2}{6}$ we are implicitly normalizing the scale of utility (Train, 2009, p.35). The difference between error terms for different alternatives i and j for individual n is assumed to follow a logistic distribution. Specifying the difference between ε_{nj} and ε_{ni} as ${\varepsilon^*}_{nji}$, we can write the cumulative distribution function of this difference as in equation (3.11).

$$F\left({\varepsilon^*}_{nji}\right) = \frac{e^{{\varepsilon^*}_{nji}}}{1 + e^{{\varepsilon^*}_{nji}}} \tag{3.11}$$

3.2.2 Choice Probabilities

The assumptions made about the unobserved part of utility in the logit model makes it possible to express choice probabilities in closed form as shown in equation (3.12).

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_{j=1}^{J} e^{V_{nj}}} = \frac{e^{\beta x_{ni}}}{\sum_{j=1}^{J} e^{\beta x_{nj}}} \tag{3.12}$$

$V_{ni} = \beta x_{ni}$ denotes the representative utility for individual n choosing alternative i. Adding up choice probabilities for all alternatives for an individual from this equation gives $\sum_{i=1}^{J} P_{ni} = 1$, i.e. the sum of choice probabilities add up to 1.

It is readily seen that choice probabilities in the logit model are functions of the explanatory variable vector x, and the corresponding parameter vector β. However, it still remains to explain how to estimate these parameters. It turns out that maximum likelihood estimation is the way to proceed (Train, 2009, p.60).

3.2.3 Maximum Likelihood Estimation

First, one must find the probability of individual n choosing the alternative she was observed to choose. If y_{ni} indicates whether the alternative was chosen or not, this can be expressed as in equation (3.13).

$$\prod_{i=1}^{J} \left(\frac{e^{\beta x_{ni}}}{\sum_{j=1}^{J} e^{\beta x_{nj}}} \right)^{y_{ni}} \tag{3.13}$$

An equivalent way of writing it is shown in equation (3.14).

$$\prod_{i=1}^{J}(P_{ni})^{y_{ni}} \tag{3.14}$$

Here, $y_{ni} = 1$ for the chosen alternative and $y_{ni} = 0$ for all other alternatives. Then it is easy to formulate an expression for the probability of every individual in the sample choosing the alternative they were observed to choose. This is called the likelihood function $L(\beta)$, and is calculated by multiplying choice probabilities for the observed choices over all individuals.

$$L(\beta) = \prod_{n=1}^{N}\prod_{i=1}^{J}(P_{ni})^{y_{ni}} \tag{3.15}$$

The estimators β that maximize this function are the maximum likelihood estimators. Maximizing the likelihood function is equivalent to maximizing the logarithm of the likelihood function (Biørn, 2010, p.18). Taking the logarithm of this expression yields the log-likelihood function, denoted as $LL(\beta)$.

$$LL(\beta) = \sum_{n=1}^{N}\sum_{i=1}^{J} y_{ni} \ln P_{ni} \tag{3.16}$$

The log-likelihood function is globally concave (Train, 2009, p.61). Therefore, it is possible to find the vector of parameters β that maximizes the log-likelihood function by finding the first order condition for each parameter.

$$\frac{\partial LL(\beta)}{\partial \beta} = 0 \tag{3.17}$$

Train (2009) shows how this can be written as in equation (3.18).

$$\frac{\partial LL(\beta)}{\partial \beta} = \sum_{n=1}^{N}\sum_{i=1}^{J}(y_{ni} - P_{ni})x_{ni} = 0 \tag{3.18}$$

It is possible to manipulate this expression for easier interpretation.

$$\frac{1}{N}\sum_{n=1}^{N}\sum_{i=1}^{J} y_{ni}x_{ni} = \frac{1}{N}\sum_{n=1}^{N}\sum_{i=1}^{J} P_{ni}x_{ni} \tag{3.19}$$

The left hand side of equation (3.19) can be seen as the observed average value of the explanatory variable vector x of the sampled decision makers. The right hand side can be read as the average of x for the predicted choices of the sampled decision makers. Thus, the maximum likelihood estimates for β are those that make the predicted average of each explanatory variable equal to the observed average in the sample (Train, 2009, p.62).

3.2.4 An Example

A simple example will show how a logit model can be used to estimate VTTS. Consider a model where the explanatory variables are travel time and travel cost. The utility of an alternative can be expressed as in equation (3.20).

$$U = \beta_t t + \beta_c c + \varepsilon \tag{3.20}$$

In this equation, t denotes travel time and c is the corresponding cost of travel. Taking the derivative of this equation with respect to t and c gives the marginal utility with respect to cost and travel time.

$$\frac{\partial U}{\partial t} = \beta_t \tag{3.21}$$

$$\frac{\partial U}{\partial c} = \beta_c \tag{3.22}$$

Dividing these two marginal utilities with each other gives equation (3.23).

$$\frac{\frac{\partial U}{\partial t}}{\frac{\partial U}{\partial c}} = \frac{\beta_t}{\beta_c} \tag{3.23}$$

This expression says that the ratio between the marginal utilities of time and money should equal the ratio between the parameters for those variables. That means β_t/β_c can be interpreted as VTTS. If log-likelihood estimation gave estimated values $\beta_t = -0.2$ and $\beta_c = -0.1$, this will give a value of 2 for the right hand side of the equation. Furthermore, if t is measured in minutes and c is measured in Norwegian kroner (NOK), this can be interpreted that an individual is willing to pay 2 NOK to save 1 minute of travel time. In this numerical example VTTS per hour would then be 120 NOK.

3.2.5 Issues in the Estimation of Logit Models

Train (2009) describes three situations that can cause problems for the estimation of the logit model. The first of these is taste variation. The logit model can represent taste variation for observed characteristics of an individual, but cannot represent taste variation for the unobserved characteristics of an individual. For example, if the researcher can observe income or age of the individuals in his sample, it is possible to let these variables interact with the different parameters of the utility function. By doing this it is possible to allow for the possibility that taste might differ for individuals with different incomes and different age. However, if there is some random part making the variables unobservable for the researcher, the logit model will be a misspecification. This will make the error terms in the utility functions correlated. As already mentioned,the logit model demands the errors terms to be distributed independently and identically.

A second situation is what Train (2009) refers to as substitution patterns. In the logit model, the introduction of a new alternative that is a close substitute to one of the alternatives already present in the choice set will cause choice probabilities to be incorrect. The red-bus-blue-bus example as presented by Train (2009) elaborates on this problem. In this example, an individual originally choose between travelling by car and travelling by a red bus. Then a new alternative is introduced making it possible for the individual to also travel by a blue bus. In the logit model, the introduction of the blue bus alternative will cause the probability of choosing car as mode of transport decline. The total probability of choosing bus as mode of transport will increase. This is because of The Property of Independence from Irrelevant Alternatives (IIA), stating that the ratio of choice probabilities in the logit model only depends on the two alternatives that are being considered. In the red-bus-blue-bus problem, the IIA property causes the logit model to overestimate the probability of travelling by either of the buses, and underestimates the probability of travelling by car (Train, 2009: p.46).

The third and last situation is concerned with panel data. The logit model will suffice if the unobserved factors that affect decision makers are independent over repeated choices. However, the logit model is not suitable for handling situations where unobserved factors are correlated over time. This is often the case in stated preference choice experiments where it is quite likely that the unobserved factors of a single respondent will be correlated over a series of choices.

The logit model is popular in use due to its simplicity. But as the discussion above shows, using a logit model can in many instances lead to biased estimates. With the advent of greater computer processing power, there has been a shift from using the logit model to using the more advanced mixed logit model.

3.3 The Mixed Logit Model

3.3.1 Choice Probabilities

The mixed logit model can alleviate the potential problems occurring in the logit model. This model is based on the same principles as the logit model, but choice probabilities obtained in the mixed logit model cannot be expressed in closed form like they were in the logit model. Let $L_{ni}(\beta)$ denote the standard logit probability evaluated at some parameter vector β. As shown earlier, this can be written as in equation (3.24).

$$L_{ni}(\beta) = \frac{e^{\beta' x_{ni}}}{\sum_{j=1}^{J} e^{\beta' x_{nj}}} \tag{3.24}$$

Mixed logit probabilities are the integrals of standard logit probabilities over a density of parameters (Train, 2009: p.135). In this model, we are assuming that the parameter vector β is different for each individual in the population. Moreover, we presume that the parameters are distributed within the population with a density $f(\beta)$. Equation (3.25) gives the mixed logit probability for individual n choosing alternative i.

$$P_{ni} = \int L_{ni}(\beta) f(\beta) d\beta \tag{3.25}$$

The mixed logit probability can be interpreted as a weighted average of the standard logit probability for different sets of parameters β.

3.3.2 The Mixing Distribution

The weights attached to different parameter sets are given by the density $f(\beta)$. This density is often called the mixing distribution. The researcher himself has to make assumptions about the density of the mixing distribution he wants to use. The normal, lognormal, uniform, triangular, gamma, or any other distribution is a potential candidate (Train, 2009: p.136). By specifying a distributional form for the parameters β, it is possible to estimate the mean and covariance of that distribution. Thus, there are two different sets of parameters in the mixed logit model. From the standard logit formula $L_{ni}(\beta)$ we have a set of parameters β. These parameters are specified to follow some density $f(\beta|\theta)$. A second set of parameters θ describe the mean and covariance of that density (Train, 2009: p.136).

3.3.3 Representative Utility with Individual-Specific Parameters

Returning to the representative utility framework explained earlier we can set up the utility of individual n choosing alternative j as in equation (3.26).

$$U_{nj} = \beta'_n x_{nj} + \varepsilon_{nj} \tag{3.26}$$

The new element here compared to the standard logit model is that we let the vector of parameters β vary between individuals. This is in contrast to the standard logit model where β was assumed to be fixed and equal for all individuals. β_n can be seen as an individual-specific parameter vector for person n. By letting the parameters vary from person to person it is possible to create taste variation among individuals.

3.3.4 Estimation by Simulation

After the distributional form of the density $f(\beta)$ has been chosen by the researcher, it is possible to use simulation to estimate the parameters θ of this density. There is a three-step procedure to follow in order to obtain choice probabilities in the mixed logit model (Train, 2009: p.144).

1. Draw a value of β from $f(\beta)$. Label it β^r with r=1 denoting the first draw
2. Calculate the standard logit formula $L_{ni}(\beta^r)$ from this draw
3. Repeat step 1 and 2 many times, and average the results

Averaging the results will give the simulated probability. Let's say there has been a number of R draws. The simulated probability of individual n choosing alternative i can then be written as in equation (3.27).

$$\hat{P}_{ni} = \frac{1}{R}\sum_{r=1}^{R} L_{ni}(\beta^r) \tag{3.27}$$

It is then possible to calculate the simulated log-likelihood function by using all the simulated probabilities.

$$SLL = \sum_{n=1}^{N} \sum_{j=1}^{J} d_{nj} \ln \hat{P}_{nj} \tag{3.28}$$

In equation (3.28) $d_{nj} = 1$ indicates that individual n chose alternative j. Correspondingly, $d_{nj} = 0$ means that individual n did not choose alternative j. The maximum simulated likelihood estimator (MSLE) is the value of the parameters of the density $f(\beta)$, such as the mean and covariance, that maximizes SLL (Train, 2009: p.144).

This chapter has focused on the logit model and the mixed logit model. A vast amount of VTTS studies have been conducted using these two types of discrete choice models. The next chapter proceeds by presenting empirical results from some of these studies.

4 Empirical Evidence

4.1 From Economic Theory to Empirical Methods

The work of economists such as Becker (1965), DeSerpa (1971), and others, has made it possible to develop sophisticated methods to estimate VTTS. They established the theoretical foundation for empirically measuring VTTS. As discussed in Chapter 2, VTTS is a function of the wage rate. Becker (1965) proposed that VTTS should be set equal to the wage rate, while the more sophisticated approach of DeSerpa (1971) suggested that VTTS could be different from the wage rate. Mackie et al. (2001) argues that VTTS should not be set equal to the wage rate for several reasons. They claim that the wage rate should be adjusted for taxes since after-tax income is the disposable income of an individual. Further, workers often earn money income on behalf of their families. On average, the wage rate must be spread across non-wage earners in the household. Thus, VTTS is likely to be more related to household disposable income rather than an individual's income. It is not always possible for an individual to allocate time efficiently as the theoretical framework proposes. Institutional constraints such as the eight hour working day make it difficult for the individual to allocate time freely. This might also affect VTTS. Finally, the content of the trip might also affect VTTS. For example, if it is possible for an individual to use her laptop or listen to music during the trip, this will make the trip less unpleasant and cause VTTS to decrease.

By collecting data on travel choices made by individuals in a population, it is possible to use discrete choice models such as the mixed logit to estimate VTTS. This is equivalent to finding K_i/λ in DeSerpa's model. There are two ways these data can be collected. One method is for the researcher to observe actual travel choices made by individuals. This is called the revealed preference approach. The second alternative is to construct a choice experiment where the respondent has to make hypothetical choices between trips with different attributes such as travel time and cost. This is called a stated preference experiment. In recent years the stated preference method has by far become the more popular of the two (Wardman, 2009: p.6). The reason for this is that the researcher has the possibility to construct alternatives with a larger set of attribute mixes than what is possible to observe with the revealed preference approach (Hensher, 2007, p.8).

4.2 The Value of Time Over Time

It turns out that income elasticity is the key to predicting future values of VTTS. Income elasticity is defined by Varian (2006, p.281) to be

$$Income\ elasticity = \frac{\%\ change\ in\ quantity}{\%\ change\ in\ income} = \frac{\frac{\Delta quantity}{quantity}}{\frac{\Delta income}{income}} \tag{4.1}$$

This is a measure for how the quantity demanded of a good responds to changes in income. In the case of measuring income elasticity of VTTS, this can be written as in equation (4.2).

$$Income\ elasticity = \frac{\%\ change\ in\ VTTS}{\%\ change\ in\ income} = \frac{\frac{\Delta VTTS}{VTTS}}{\frac{\Delta income}{income}} \tag{4.2}$$

4.2.1 Measuring Income Elasticity of VTTS

The traditional approach is to treat VTTS as a function of the average wage rate, and adjust VTTS proportionally to increases in the wage rate (Hensher, 2007, p.11). This implies an income elasticity of VTTS equal to 1. However, as Hensher (2007) and Wardman (2001) remarks, there are no obvious reasons why this should be the correct estimate of income elasticity. From the theoretical point of view, VTTS is interpreted as the ratio between the marginal utility of time and the marginal utility of income. A traditional stand in microeconomics is that the marginal utility of income is decreasing in income. However, it is not possible to make a similar statement regarding the marginal utility of time. While it is quite certain that VTTS increases with income, there is no theoretical support that the increase in VTTS should be proportional to the increase in income.

4.2.2 Cross-Sectional and Longitudinal Data

There are two methods of measuring income elasticity empirically. One possibility is to calculate income elasticity from cross-sectional data within a study. The income elasticity derived across decision makers in a population at a certain point in time would then be the estimate of how VTTS varies over time with income growth (Wardman, 2001, p.5). Hensher (2007, p.12) find evidence from a range of different empirical work that this method of calculating income elasticity yields values for income elasticity lower than 1. Most estimates are between 0.25 and 0.75.

The other method is to calculate income elasticity from longitudinal data between studies. This amounts to looking at VTTS derived from studies conducted at different points in time, and comparing it with the corresponding growth in income over that time period. In a meta-analysis by Wardman and Abrantes (2009), comparing 226 different studies conducted over a span of 45 years yields a longitudinal income elasticity of 0.9. This is remarkably higher than the cross-sectional income elasticity of 0.5 found by the same author in another meta-analysis (Wardman, 2001). It is also higher than the evidence found by Hensher (2007) for cross-sectional income elasticity. Thus, there is conflicting evidence on income elasticities found from longitudinal and cross-sectional data. Wardman (2009, p.15) argues that the longitudinal estimated income elasticity of 0.9 justifies the practice of increasing VTTS proportionally to income growth.

In the Norwegian Value of Time Study, with data collected in 2009, a cross-sectional income elasticity of 0.432 is found (Ramjerdi, 2010). The longitudinal income elasticity is calculated by using the VTTS found in this study, and comparing it with the VTTS found in a similar study with data collected in 1996 (Ramjerdi, 1997). Income growth can be approximated by using growth in GDP. The comparison results in an income elasticity of about 1.0. Thus, in line with the work of Wardman (2009), the longitudinal income elasticity of VTTS is higher than the cross-sectional income elasticity of VTTS.

Using lower values for income elasticity yields lower predictions for future VTTS. In other words, choosing to predict future VTTS with the cross-sectional income elasticity will yield a lower estimate for future VTTS than using the longitudinal income elasticity. Several papers have addressed the issue of discrepancy between cross-sectional income elasticity and longitudinal elasticity.

4.2.3 Explaining Discrepancy

Fosgereau (2005) claims that the reason why cross-sectional income elasticities of VTTS are found to be so low in many empirical studies could be that these income elasticities often are based on before-tax income of individuals, rather than after-tax income. Using data from the Danish value of time study, collected in 2004, he finds that the income elasticity of VTTS using after-tax income should be scaled by a factor of 1.26 relative to the income elasticity of before-tax income. Also controlling for travel distance, which can be seen as a variable that might depend on income, he obtain an estimate of 0.9 for the cross-sectional income elasticity. This is in fact equal to the longitudinal income elasticity found by Wardman (2009). In the Norwegian Value of Time Study after-tax income is used, but income elasticity is less than 0.5. Correcting for income tax does not help to explain the discrepancy between cross-sectional and longitudinal income elasticity for this study.

Börjesson, Fosgerau and Algers (2009) use data from the Swedish value of time studies from 1994 and 2007 to investigate how the cross-sectional income elasticity of VTTS evolves over time. A constant cross-sectional income elasticity of VTTS implies a log-linear relationship between VTTS and income. This can be written as in equation (4.3) where α denotes income elasticity.

$$\log VTTS = \alpha * \log I + \varepsilon \tag{4.3}$$

However, there is no particular reason for why income elasticity should be constant across individuals with different incomes. It is possible to address this issue by allowing for a non-linear relationship between the logarithm of VTTS and the logarithm of income. Assuming that the relationship is non-linear indicate that income elasticity of VTTS changes with income. Let f describe the non-linear function that relates income elasticity to income. The relationship between VTTS and income is then given by equation (4.4).

$$\log VTTS = f(\log I) + \varepsilon \tag{4.4}$$

The income elasticity is found as the derivative of the non-linear function, i.e. $f'(log\ I)$. Thus, rather than assuming that income elasticity is equal to α for each individual, income elasticity will be assumed to differ between individuals depending on their level of income. If in fact income elasticity is a function of income, then the average cross-sectional income elasticity will be affected by how income is distributed in the population. That is, α as given in equation (4.3) will be dependent on the income distribution.

The inter-temporal income elasticity, which is the average cross-sectional income elasticity at some future time, will be affected by how income growth and income is distributed among the population. Thus, the average income elasticity α might be different for two cross-sectional studies conducted at two different points in time.

Börjesson, Fosgerau and Algers (2009) study points to the evidence that cross-sectional income elasticity is an increasing function of income. By segmenting the population into three income groups they find that income elasticity is close to unity for the higher income groups, while it is not significantly different from zero for the lower income groups. They conclude that VTTS does not seem to be log-linear in income. Hence, the income distribution and the average income will affect the average income elasticity of VTTS (Börjesson et al., 2009, p.7). Furthermore, they find that income elasticity is stable over time within the different income segments. They speculate that the relationship between income and VTTS has not changed over time. Rather, the income distribution of the samples has changed between the two studies.

If the cross-sectional income elasticity of VTTS is stable within each income segment, this implies that the longitudinal income elasticity for each income segment is equal to unity. This results from equation 4.3 as follows

$$e^{\log VTTS_0^i} = e^{\alpha_i \log I_0} \;\; \Rightarrow VTTS_0^i = e^{\alpha_i} I_0 \qquad (4.5)$$

α_i denotes income elasticity for income segment i. Furthermore, the subscript 0 refers to time 0. Let us now look at VTTS at some future time t. If r denotes the percentage increase in income between time 0 and t for income segment i, it is possible to write VTTS at time t as in equation (4.6).

$$VTTS_t^i = e^{\alpha_i} I_0 (1 + r) \qquad (4.6)$$

A stable relationship between income and income elasticity suggests that α_i should be the same at time 0 and t. By dividing equation (4.6) with equation (4.5) it is possible to obtain a measure for the relative increase in VTTS between the two points in time.

$$\frac{VTTS_t^i}{VTTS_0^i} = \frac{e^{\alpha_i} I_0 (1 + r)}{e^{\alpha_i} I_0} = (1 + r) \qquad (4.7)$$

As can be seen from equation (4.7), the relative increase in VTTS for income segment i is equal to the relative increase in income for that income segment. Thus, the longitudinal income elasticity is equal to unity for each income segment.

In the study of Börjesson et al. (2009) the observations from the lowest income group are discarded. The authors claim that the income reported in this segment cannot be trusted at a sufficient degree of certainty. This is because individuals with very low income often rely on the income of a spouse, personal wealth or other sources that makes their own income a less relevant factor determining VTTS (Börjesson et al., 2009, p.7). As an effect, the corresponding income elasticity for this income group will be estimated incorrectly.

The focus of the rest of this thesis will be on the Norwegian Value of Time Study from 2009. An attempt will be made to explain the discrepancy between the estimated cross-sectional income elasticity of VTTS in this study, and the longitudinal income elasticity of VTTS of about 1.0 that results from the comparison of VTTS in the 1996 and 2009 study. This value is similar to the longitudinal income elasticity of 0.9 found by Wardman (2009).

5 Data

5.1 The Norwegian Value of Time Study

The Norwegian Value of Time Study (Ramjerdi, 2010) uses a stated preference (SP) design for collecting data on trade-offs between time and cost among respondents. Observations on hypothetical choices made by respondents between alternatives differing in travel time and cost make it possible to estimate VTTS. The study is divided into short distance travels and long distance travels. Short distance travels are trips shorter than 100 kilometres, while long distance travels are trips longer than 100 kilometres. The short distance travel segment investigates VTTS for car and public transport. The long distance travel segment investigates VTTS for car, rail, plane and bus. The study also incorporates VTTS estimation for walk and cycle, as well as for ferry and boat. There are three different questionnaires used for the short distance travel segment, the long distance travel segment and the walk and cycle segment respectively. Respondents only answered one of the questionnaires. In the following, the focus will be on short distance travels with trips shorter than 100 kilometres. The questionnaire used for this segment is illustrated in Figure 5.1.

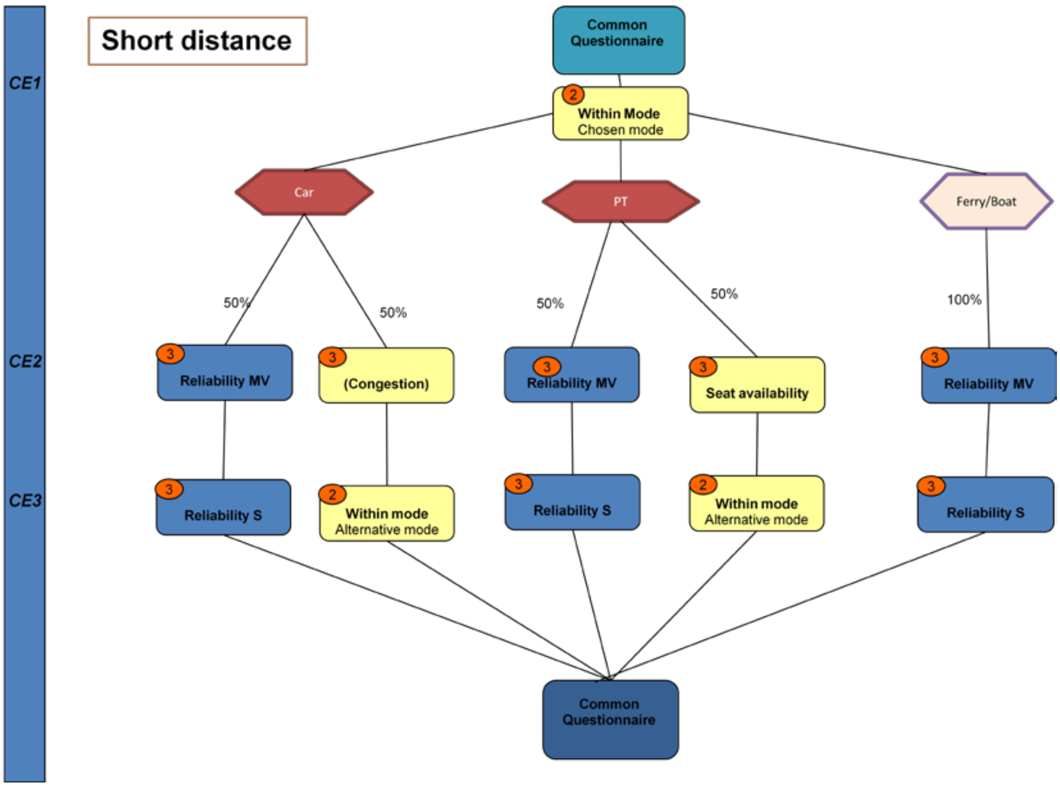


Figure 5.1: Questionnaire for Norwegian Value of Time Study

The structure of the questionnaire is as follows:

1. Introductory questionnaire to collect socio-economic and demographic data on respondents
2. Questionnaire to collect data on the reference trips of the respondents
3. Choice experiments to collect data on the trade-offs respondents make between different attributes
4. Final questionnaire to collect further data on respondents

By collecting socio-economic and demographic data, the researcher can uncover systematic variation in VTTS estimates among respondents. It is possible to create more realistic alternatives in the SP experiments by constructing a reference trip for each respondent. The SP choice experiments are designed in such a way that it is possible to estimate values for different time components of the trip. These different components are in-vehicle time, reliability of travel time, congestion, seat availability and comfort differences between modes of transport. In Figure 5.1 CE1, CE2 and CE3 denotes the different choice experiments that are used to evaluate different time components of the trip. In this thesis the focus will be on in-vehicle time for short distance car travellers. Thus, I will utilize data collected in CE1 with car chosen as mode of transport, in combination with the socioeconomic and demographic data collected from respondents in this segment. This can be illustrated as follows.

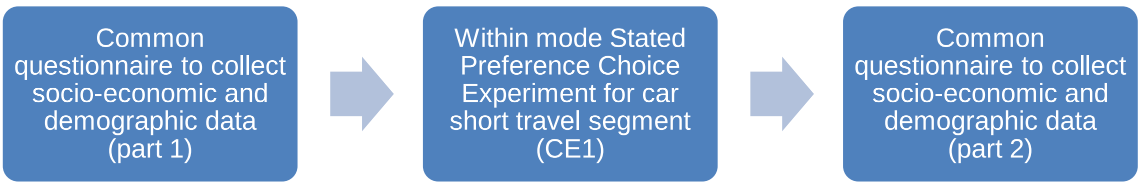


Figure 5.2: Utilization of data from the Norwegian Value of Time Study

Section 5.2 explains how socio-economic and demographic data was collected, as well as how the reference trip was created for each respondent. Section 5.3 continues by describing how the Stated Preference Choice Experiment for in-vehicle time is constructed in the Norwegian Value of Time Study. Finally, Section 5.4 describes how respondents were recruited to participate in the study.

5.2 Socio-Economic and Demographic Data

It is necessary to collect socio-economic and demographic data on the respondents of a study in order to be able to observe how VTTS vary for different parts in the population. In the Norwegian Value of Time Study a whole range of such data was collected for this purpose. Respondents were asked to state their age, gender, education level, income, occupation and region, amongst other things. In addition to the socio-economic and demographic data collected, the common questionnaire also included questions to produce a reference trip for each respondent. The respondents were asked to write a travel diary with actual trips they had made recently. One of the trips from the travel diary is chosen randomly as reference trip for each respondent. This reference trip has base time as stated in the travel diary. Base cost is computed by multiplying the distance from the reference trip with the perceived cost of travelling by car per kilometre for each respondent. The reference trip is utilized in the stated preference choice experiment CE1. Parts of the common questionnaire used in the Norwegian Value of Time Study are presented in Figure A.1-A.13 in the Appendix.

5.3 Stated Preference Choice Experiment Design

The Stated Preference Choice Experiment CE1 consists of two attributes. Respondents are asked to make nine choices from alternatives differing in travel time and cost. The choice situations are presented to the respondent as follows:

Figure 5.3: A choice situation in the stated preference experiment

The two alternatives in each choice situation are created based on the reference trip.

5.3.1 Four Types of Valuation

The trade-off between travel time and cost for respondents is measured in four different quadrants as illustrated in Figure 5.4. The origin defines the reference trip.

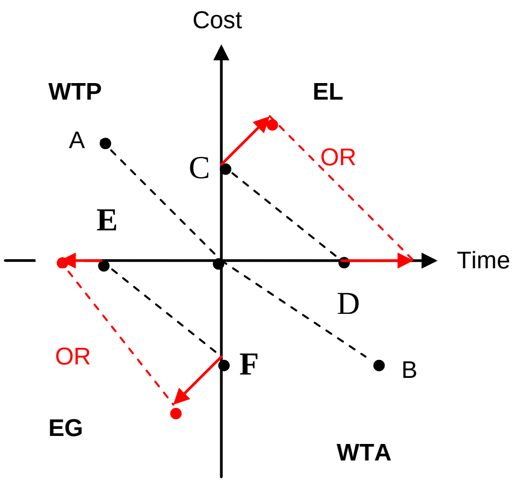


Figure 5.4: Four different types of valuations

WTP stands for willingness to pay, WTA stands for willingness to accept, EL stands for equivalent loss, EG stands for equivalent gain. The choice situations are constructed such that the respondent is exposed to all four different types of valuations. A further description is given in Figure 5.5.

WTP: One alternative is the reference trip. The other alternative is a trip with higher cost than the reference trip and shorter travel time.	**EL:** One alternative has the same travel time as the reference trip, but a higher cost. The other alternative has a longer travel time than the reference trip, but cost the same.
EG: One alternative has the same travel time as the reference trip, but cost less. The other alternative has a shorter travel time than the reference trip, but cost the same.	**WTA:** One alternative is the reference trip. The other alternative is a trip with lower cost than the reference trip and longer travel time.

Figure 5.5: Explanation of the different valuations

5.3.2 Choice Situations

Respondents are faced with eight choice situations, two for each type of valuation. In addition, respondents are also faced with an off-reference choice situation with alternatives that are derived from the reference trip. After the nine choice situations, the respondent is asked a contingent valuation question in order to reveal the respondents maximum WTP or WTA.

Eight of the choice situations are created with the reference trip as base value for travel time and cost. The alternatives of these choice situations are created for each respondent by drawing two random values from each of the four time intervals: 10-15, 15-20, 20-25 and 25-30. These numbers are treated as percentage change from the reference trip base value. From the reference travel time value it is then possible to calculate Δt as change in travel time measured in minutes. Correspondingly, there are drawn two random values from each of the four VTTS intervals: 10-50, 50-100, 100-250 and 250-500. This is measured in NOK per hour. By randomly pairing up the eight different values obtained for Δt and VTTS, it is possible to construct eight different choice situations with Δt and Δc, with Δc being the change in cost of the reference trip. This is done by utilizing VTTS and Δt as follows:

$$\Delta c = \Delta t * \left(\frac{VTTS}{60}\right) \tag{5.1}$$

The eight combinations of Δc and Δt are assigned to the WTP, WTA, EL and EG choice situations. Let t_{ref} define reference trip travel time, and let c_{ref} define reference trip cost. The different choice situations then take the form:

WTP	Travel Time	Cost
Alternative 1	t_{ref}	c_{ref}
Alternative 2	$t_{ref} - \Delta t$	$c_{ref} + \Delta c$

Figure 5.6a: A WTP choice situation

WTA	Travel Time	Cost
Alternative 1	t_{ref}	c_{ref}
Alternative 2	$t_{ref} + \Delta t$	$c_{ref} - \Delta c$

Figure 5.6b: A WTA choice situation

EL	Travel Time	Cost
Alternative 1	t_{ref}	$c_{ref} + \Delta c$
Alternative 2	$t_{ref} + \Delta t$	c_{ref}

Figure 5.6c: An EL choice situation

EG	Travel Time	Cost
Alternative 1	t_{ref}	$c_{ref} - \Delta c$
Alternative 2	$t_{ref} - \Delta t$	c_{ref}

Figure 5.6d: An EG choice situation

The OR choice situation is constructed by multiplying the travel time alternative and cost alternative by either 1.2 or 0.8, depending on whether it is EL-based or EG-based.

5.4 The Sample

A self administered internet survey method was used in the Norwegian Value of Time Study. A total of 47000 persons were contacted to participate. Out of these, 9280 persons responded, giving a response rate close to 20%. The survey was conducted between June 11th and July 2nd 2009. As some of the modes of transport had a low response rate, an additional survey was conducted, giving a total of 9417 respondents. After cleaning the data, 8744 respondents remained. These respondents were assigned to different questionnaires for short distance travel, long distance travel and walk/cycle. Figure 5.7 provides an overview.

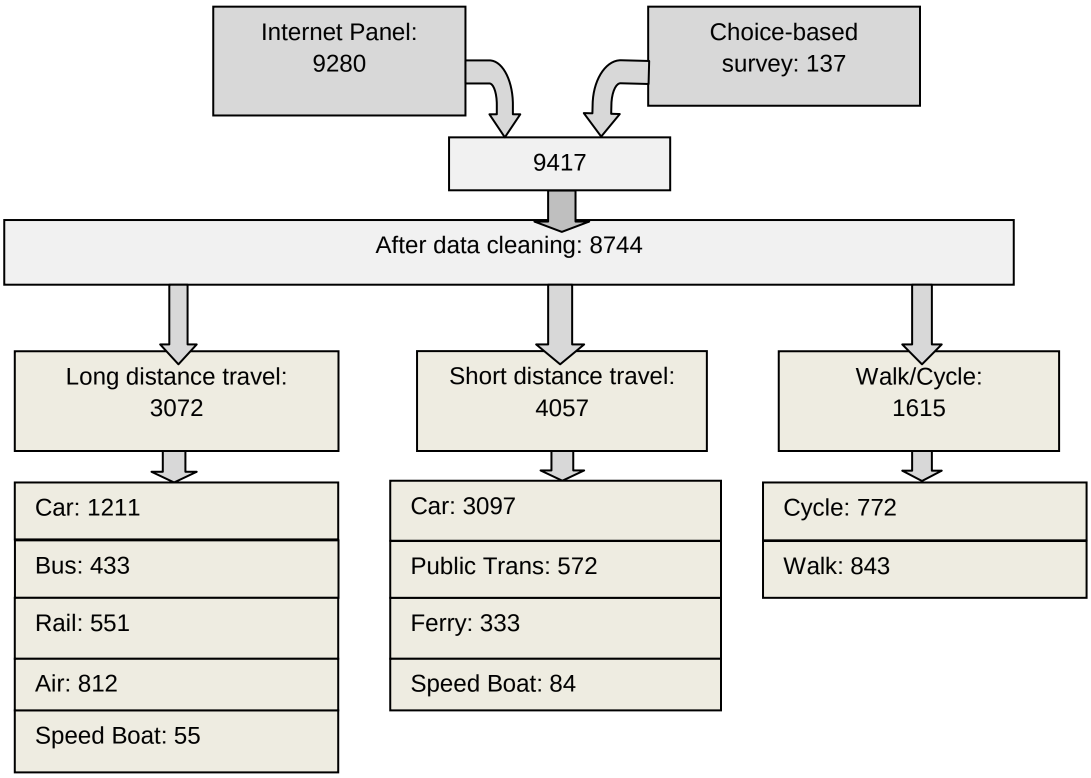


Figure 5.7: Overview of respondents

As can be seen from this figure, 4057 respondents were assigned to the short distance travel questionnaire. Out of these, 3097 answered were assigned car as mode of transport. It is data from these 3097 respondents that is utilized in this thesis.

A mixed logit model as described in Section 3.3 is applied to the data set in order to perform estimation. The next chapter explains how the mixed logit model is formulated in the Norwegian Value of Time Study.

6 Econometric Model Formulation

6.1 Estimating VTTS with Mixed Logit

In a standard mixed logit model the indirect utility of an alternative can be written as in equation (6.1).

$$U = \beta_C C + \beta_T T + \varepsilon \tag{6.1}$$

β_C and β_T are the parameters for cost and time respectively. As explained in Chapter 3, when a mixed logit model is used, the parameters for time and cost are assumed to differ between individuals in the population because of taste variation. Thus, it is not possible to simply put VTTS equal to the ratio β_T/β_C. Rather, it is the expectation of this ratio, $E[\beta_T/\beta_C]$, that will give the estimated VTTS for the population. However, estimating VTTS this way is difficult. The estimate is also very sensitive to the assumptions made regarding the distribution of the random parameters (Fosgerau, Hjorth & Lyk-Jensen, 2007, p.3).

6.1.1 A Single Mixing Distribution

It is possible to alleviate the problem with highly sensitive estimates for VTTS in the mixed logit model. Fosgerau et al. (2007) formulates a mixed logit model in terms of equation (6.2).

$$\log w = \log\left(\frac{\beta_T}{\beta_C}\right) \tag{6.2}$$

This makes it possible to use a single mixing distribution rather than two separate mixing distributions for β_T and β_C. By using a single mixing distribution it is less likely that the model is specified incorrectly.

The model by Fosgerau et al. (2007) is used for estimation in the Norwegian Value of Time Study. The estimation is based on data from the stated preference experiment as explained in Section 5.3. Each choice situation in the stated preference experiment involves a trade-off between time and cost. Let $|\Delta C| = |C_1 - C_2|$ denote the difference in cost between the alternatives. Similarly, let $|\Delta T| = |T_1 - T_2|$ denote the difference in travel time between the alternatives. For each choice situation, $|\Delta C|/|\Delta T|$ will be the rate of trade-off between money and time presented to the respondent. It is convenient to represent this trade-off as a logarithm as well.

$$\log v = log\left(\frac{|\Delta C|}{|\Delta T|}\right) \tag{6.3}$$

Whether this bid will be accepted or not depends on the individual's VTTS, defined as β_T/β_C. Consider alternative 1 to be the fast and expensive alternative, while alternative 2 is the slow and cheap alternative. A respondent n in choice situation j will choose alternative 1 whenever her β_T/β_C is higher than $|\Delta C|/|\Delta T|$. Suppose that $y_{nj} = 1$ means that the fast and expensive alternative is chosen. It is possible to write this as in equation (6.4).

$$y_{nj} = 1 \rightarrow \log\left(\frac{\beta_T}{\beta_C}\right)_{nj} + \frac{\varepsilon_{nj}}{\mu} > log\left(\frac{|\Delta C|}{|\Delta T|}\right)_{nj} \tag{6.4}$$

An equivalent statement is given in equation (6.5).

$$y_{nj} = 1 \rightarrow \log(w)_{nj} + \frac{\varepsilon_{nj}}{\mu} > log(v)_{nj} \tag{6.5}$$

The error term ε_{nj} is a logistic random variable with mean zero and scale μ. It is possible to decompose w in such a way that

$$\log(w)_{nj} = \delta X_{nj} + u_n \tag{6.6}$$

The systematic part of this expression represents observed heterogeneity in VTTS among respondents with X being a vector of background and trip variables, and δ being the corresponding vector of parameters. The random variable u is unobserved heterogeneity. This variable has mean zero. It is constant across observations from the same individual. Thus, alternative 1 is chosen whenever equation (6.7) holds.

$$y_{nj} = 1 \rightarrow \delta X_{nj} + u_n + \frac{\varepsilon_{nj}}{\mu} > log(v)_{nj} \tag{6.7}$$

This is the formulation of the mixed logit model, where u represents the mixing distribution. The distribution chosen for u determines the distribution of w, conditional on the explanatory variables X. The model formulation of Fosgereau et al. (2007) makes it possible to work directly with the distribution of VTTS rather than with a ratio of random parameters.

6.1.2 Choice Probabilities

Choice probabilities related to each choice situation can be derived. Consider the case where the slow and cheap alternative is chosen, denoted as $y_{nj} = 2$.

$$y_{nj} = 2 \rightarrow \delta X_{nj} + u_n + \frac{\varepsilon_{nj}}{\mu} < log(v)_{nj} \tag{6.8}$$

Assume that the value of u_n is given. Then, the probability for the slow and cheap alternative to be chosen is given by equation (6.9).

$$P(y_{nj} = 2|u_n) = \varepsilon_{nj} < \mu\left[log(v)_{nj} - \delta X_{nj} - u_n\right] \tag{6.9}$$

It is also possible to state this as a cumulative distribution function F.

$$P(y_{nj} = 2|u_n) = F_{\varepsilon_{nj}}\left(\mu\left[log(v)_{nj} - \delta X_{nj} - u_n\right]\right) \tag{6.10}$$

By construction, the error term in a mixed logit model is logistically distributed. Thus, it is possible to calculate the mixed logit probabilities for an individual n in choice situation j given u_n. This is shown in equation (6.11) and (6.12) for the slow and fast alternative respectively.

$$P(y_{nj} = 2|u_n) = \frac{1}{1 + e^{-\mu\left[log(v)_{nj} - \delta X_{nj} - u_n\right]}} \tag{6.11}$$

$$P(y_{nj} = 1|u_n) = \frac{e^{-\mu\left[log(v)_{nj} - \delta X_{nj} - u_n\right]}}{1 + e^{-\mu\left[log(v)_{nj} - \delta X_{nj} - u_n\right]}} \tag{6.12}$$

The exposition above constitutes the framework that estimation of VTTS in the Norwegian Value of Time Study is based on. This framework can also be modified such that it takes into account that many people exhibit loss aversion in choice situations (Tversky and Kahneman, 1992).

6.2 Reference-dependent Preferences

6.2.1 The Value Function

Tversky and Kahneman (1992) claim that reference levels play a large role in determining preferences. They define what is called a value function, which is important in how people valuate losses and gains from a given reference point. A vast amount of empirical evidence is presented indicating that people tend to be loss averse in many choice situations. For this reason, the value function is steeper for losses than for gains. However, the marginal value of both losses and gains decreases with their size. Thus, loss aversion is only present in situations where the gains and losses involved are small. This can be seen from Figure 6.1.

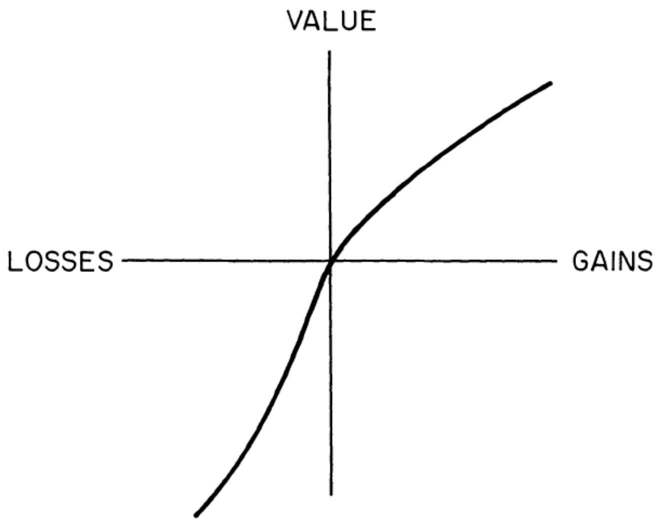


Figure 6.1: The value function (Source: Tversky & Kahneman)

Loss aversion has an effect on how people behave. It can cause an endowment effect in that the loss of utility of giving up a good is greater than the utility obtained by receiving it. Another consequence of loss aversion is a status quo bias. Loss aversion induces a bias that favors the retention of the status quo over other options (Tversky & Kahneman, 1992, p.1042). The authors argue that loss aversion could be an important factor in explaining the often seen discrepancy between willingness to pay (WTP) and willingness to accept (WTA).

6.2.2 Introducing Loss Aversion in the Econometric Model

De Borger and Fosgerau (2008) have developed a method to incorporate the effect of reference-dependent preferences and loss aversion in the estimation of VTTS. By using information on four different types of binary choices between travel time and cost, they find that a model implying reference-dependent preferences cannot be rejected against more general alternatives. The four types of valuations are willingness to pay (WTP), willingness to accept (WTA), equivalent gain (EG) and equivalent loss (EL), as explained in Section 5.3. The result of the analysis of De Borger and Fosgerau (2008) is that travellers attach a larger value to a time loss than to a time gain. Similarly, an increase in cost will give a larger utility loss than the utility gained by a decrease in cost.

The Norwegian Value of Time Study utilizes the method of De Borger and Fosgerau (2008) to capture the effect of loss aversion. First, value functions for travel time and cost are defined as in equation (6.13) and (6.14).

$$v(C) = |\Delta C| e^{\eta_C S(C)} \tag{6.13}$$

$$v(T) = |\Delta T| e^{\eta_T S(T)} \tag{6.14}$$

$S(C) = \Delta C / |\Delta C|$ and $S(T) = \Delta T / |\Delta T|$ describes whether the changes in attributes are gains or losses from the reference trip. A positive $S(C)$ and negative $S(T)$ indicate a WTP choice situation, while the reverse indicate a WTA choice situation. For an EL choice situation, one alternative will have positive $S(C)$ and the other will have positive $S(T)$. For an EG choice situation, one alternative will have negative $S(C)$ while the other will have negative $S(T)$. This can also be seen from Figure 5.15. The parameters η_C and η_T describe loss aversion. The value functions can be implemented in the econometric framework of VTTS estimation. Then losses and gains relative to the reference trip of a respondent are weighted by the value functions.

As before, a respondent will choose the slow and cheap alternative 2 whenever her VTTS is lower than the offer in the choice situation. With loss aversion this can be written like

$$\left(\frac{\beta_T}{\beta_C}\right)_{nj} < \frac{|\Delta C| e^{\eta_C S(C)}}{|\Delta T| e^{\eta_T S(T)}} \tag{6.15}$$

Using the framework as explained in Section 6.1, the following two equations are utilized.

$$\log\left(\frac{\beta_T}{\beta_C}\right)_{nj} = \log(w)_{nj} = \delta X_{nj} + u_n \tag{6.16}$$

$$log\left(\frac{|\Delta C|}{|\Delta T|}\right)_{nj} = \log(v)_{nj} \quad (6.17)$$

Taking the logarithm on both sides of equation (6.15) gives equation (6.18).

$$y_{nj} = 2 \rightarrow \delta X_{nj} + u_n + \frac{\varepsilon_{nj}}{\mu} < log(v)_{nj} + \eta_C S(C) - \eta_T S(T) \quad (6.18)$$

Then it is possible to derive choice probabilities for each of the alternatives. The probability for respondent n choosing the slow and cheap alternative 2 in choice situation j is given by equation (6.19).

$$P(y_{nj} = 2|u_n) = \varepsilon_{nj} < \mu\left[log(v)_{nj} + \eta_C S(C) - \eta_T S(T) - \delta X_{nj} - u_n\right] \quad (6.19)$$

Again, this can be stated as a cumulative distribution function F.

$$P(y_{nj} = 2|u_n) = F_{\varepsilon_{nj}}\left(\mu\left[log(v)_{nj} + \eta_C S(C) - \eta_T S(T) - \delta X_{nj} - u_n\right]\right) \quad (6.20)$$

Since the error term is logistically distributed, this can be written as in equation (6.21).

$$P(y_{nj} = 2|u_n) = \frac{1}{1 + e^{-\mu\left[log(v)_{nj} + \eta_C S(C) - \eta_T S(T) - \delta X_{nj} - u_n\right]}} \quad (6.21)$$

Correspondingly, the choice probability for the fast and expensive alternative to be chosen is given by equation (6.22).

$$P(y_{nj} = 1|u_n) = \frac{e^{-\mu\left[log(v)_{nj} + \eta_C S(C) - \eta_T S(T) - \delta X_{nj} - u_n\right]}}{1 + e^{-\mu\left[log(v)_{nj} + \eta_C S(C) - \eta_T S(T) - \delta X_{nj} - u_n\right]}} \quad (6.22)$$

If in fact η_c and η_t are found to be significantly different from zero, respondents can be considered to exhibit loss aversion. VTTS will then vary whether the alternative is presented as a gain or a loss from the reference trip. The stated choice experiment CE1, as explained in Section 5.3, is constructed such that it is possible to estimate these parameters.

By introducing loss aversion to the mixed logit model as presented in Section 6.1, it is possible to differentiate between gains and losses from the reference trip when estimating VTTS. This will improve the model if the parameters estimated are found to be significant.

However, it is possible to improve the model further by testing whether the assumed form for the mixing distribution of u is correct.

6.3 The Choice of Mixing Distribution

Specifying an incorrect form for the mixing distribution might have serious consequences for the purpose of estimating VTTS. At the outset, a log-normal distribution for u is suggested in the Norwegian Value of Time Study. Fosgerau and Bierlaire (2007) have developed a test based on semi-nonparametric (SNP) techniques to examine whether the mixing distribution chosen is correct or not. If a log-normal mixing distribution is used, this is tested against a generalized mixing distribution. If the generalized mixing distribution provides a better fit than the log-normal mixing distribution, the log-normal mixing distribution is discarded in favour of the generalized mixing distribution.

Following Fosgerau and Bierlaire (2007), the true probability density function of the mixing distribution u can be written as in equation (6.23).

$$g(u) = q\big(F(u)\big)f(u) \tag{6.23}$$

In this equation, q transform the log-normal mixing distribution given by the cumulative distribution function $F(u)$ and the probability density function $f(u)$, into the generalized mixing distribution $g(u)$. The SNP technique involves using a series of Legendre polynomials to estimate q. Further details on how to perform this estimation are given in Fosgerau and Bierlaire (2007).

The researcher specifies how many SNP terms he wants to include in the series. Parameters for these terms can be estimated. If the null hypothesis of log-normal mixing distribution is correct, we have $f(u) = g(u)$. This implies that $q = 1$. Then, none of the estimated SNP parameters will be significantly different from zero. In the Norwegian Value of Time Study a number of four SNP terms is used. Inclusion of these terms turns out to increase the explanatory power of the model, as one of them is significantly different from zero. Thus, rather than using a log-normal mixing distribution, the alternative generalized mixed distribution is applied.

7 Estimation Results

7.1 Biogeme

Estimation in the Norwegian Value of Time Study was carried out using Biogeme version 1.7 (Bierlaire, 2008). Biogeme is an open source freeware designed for the estimation of discrete choice models.

7.1.1 Model Specification File

It is required to write a model specification file to be able to perform estimation in Biogeme. By modifying the model specification file used in the Norwegian Value of Time Study (Ramjerdi, 2010), it is possible to estimate a whole range of models using different explanatory variables and segments of data.

The model specification file in Biogeme is written such that utilities for the two alternatives in each choice situation are specified as in Figure 7.1.

Alternative 1	$\log(w)_{nj} = \delta X_{nj} + \eta_T S(T) - \eta_C S(C) + u_n$
Alternative 2	$\log(v)_{nj} = log\left(\frac{\lvert\Delta C\rvert}{\lvert\Delta T\rvert}\right)_{nj}$

Figure 7.1: Alternatives with corresponding utilities for each choice situation

7.1.2 Report File

Biogeme (Bierlaire, 2008) produces a report file with an overview of the results from model estimation. The report file starts by providing general information about the estimated model.

- Number of Halton draws
    - This refers to the number of simulated draws from the density of the individual-specific parameter as explained in Section 3.3.4.

- Number of observations and Number of individuals

- Number of the individuals refers to the number of respondents in the sample. Since each respondent face several choice situations, the number of observations will be higher than the number of individuals.

- Null log-likelihood
  - Log-likelihood of the sampled respondents if all parameters are set equal to zero.

- Final log-likelihood
  - The maximum simulated log-likelihood of the sample for the estimated model.

- Likelihood ratio test
  - Let L_0 denote the null log-likelihood and L^* denote the final log-likelihood. The likelihood ratio test is then: $-2(L_0 - L^*)$. This is a test-statistic that is used to test the null hypothesis that all parameters are zero. It is asymptotically distributed chi-square (Ben-Akiva & Lerman, 1985).

- Adjusted rho-square
  - Let ρ^2 denote the adjusted rho-square and K the number of estimated parameters. It can then be written as $\rho^2 = 1 - \frac{L^* - K}{L_0}$. If the estimated parameters do no better than zero parameters, ρ^2 will be equal to zero. On the other hand, if the estimated model is so good that each sampled decision maker's choice could be perfectly predicted, ρ^2 will be equal to one.

The estimated parameters for the explanatory variables X, as well as parameters accounting for reference-dependent preferences, explain observed heterogeneity in VTTS among respondents. The random and individual-specific variable u explains unobserved heterogeneity in VTTS. A further explanation on the estimated parameters as they appear in the Biogeme report file is provided in Section 7.2.3.

By letting explanatory variables enter as logarithms in the model, the estimated parameters can be interpreted as elasticities with respect to VTTS. Thus, using the logarithm of income as one of the explanatory variables makes it possible to estimate income elasticity of VTTS directly. For the dummy parameters in the model, the explanatory variables are linear. If δ_k

denotes a dummy parameter, the estimate $e^{\delta_k} - 1$ can be interpreted as percentage change in VTTS.

Section 7.2 continues by presenting the Extended Base Model used for estimation in this thesis. Section 7.3 provides an investigation of how income elasticity varies with income in the Extended Base Model. Section 7.4 presents the estimation results for other types of segmentation based on the Extended Base Model. Finally, Section 7.5 summarizes.

7.2 The Extended Base Model

The Extended Base Model is a modification of the Base Model used in the Norwegian Value of Time Study. As mentioned in Chapter 5, this thesis will focus on the car short distance travel segment with data collected for the Norwegian Value of Time Study. At the outset, a closer look at the socio-economic and demographic data describing this segment is warranted. This makes it possible to get a better understanding of who the respondents in the study are.

7.2.1 Socio-economic and Demographic Data

A detailed description on how socio-economic and demographic data was collected in the Norwegian Value of Time Study can be found in Section 5.3. Figure 7.2 provides an overview of the basic characteristics of the respondents in the car short distance travel segment.

Female	Mean Age	Mean Income	Sample Size
43.75%	46.47	312562	3097

Figure 7.2: Share of females, mean age, mean income and sample size

Income

It is of interest to point to the difficulties of collecting data on income. Respondents usually do not like to reveal their exact personal incomes or household incomes. This is the reason for asking the respondents to state their personal and household incomes in income brackets. The real disposable income of respondents might also be different from the wage income due to transfers and other sources of income. Hence, personal income after tax is only a proxy to the real disposable income of respondents. A further issue is whether one should use personal disposable income or disposable household income adjusted for household size. The same qualification applies to disposable household income adjusted for household size. Data on personal income is most likely more reliable than the data on household income. The missing data on household income is significantly higher than personal income. Therefore, it is common to rely on personal income after tax in similar studies.

Mean after-tax income is calculated for the respondents who had stated their pre-tax personal income. This constitutes 95% of the sample. The stated pre-tax incomes were converted to after-tax incomes by applying Norwegian tax rates. The distribution of after-tax incomes is depicted in the Figure 7.3. Income is measured in thousands of NOK along the horizontal axis. The shape of this distribution resembles a log-normal distribution. This justifies the initial assumption that u also might be log-normally distributed conditional on the explanatory variables.

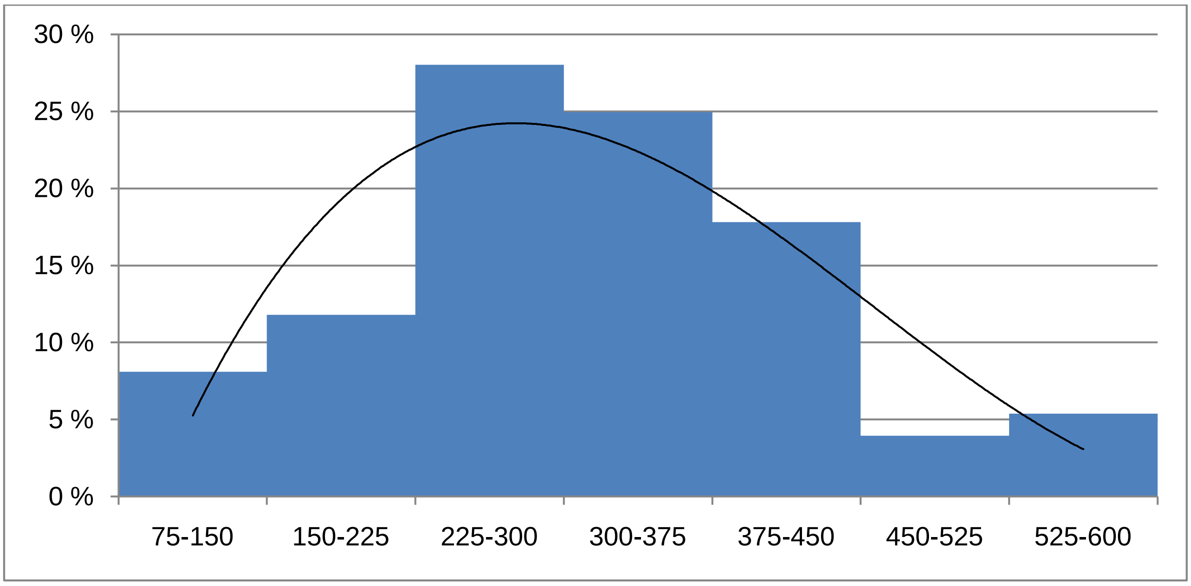


Figure 7.3: Income distribution for the car short distance travel segment

Age

The age of the respondents in the car short distance travel segment is distributed as shown in Figure 7.4. Values on the horizontal axis denote age. A comparison of this distribution with the true age distribution for the Norwegian population (SSB 2011) shows that young people are slightly underrepresented in the car short distance travel segment.

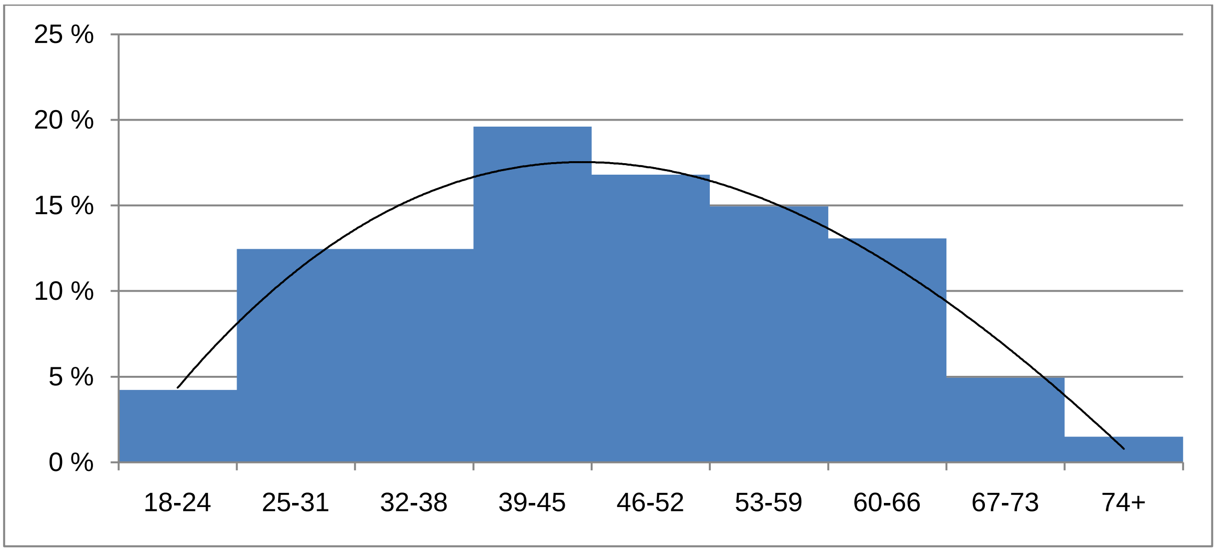
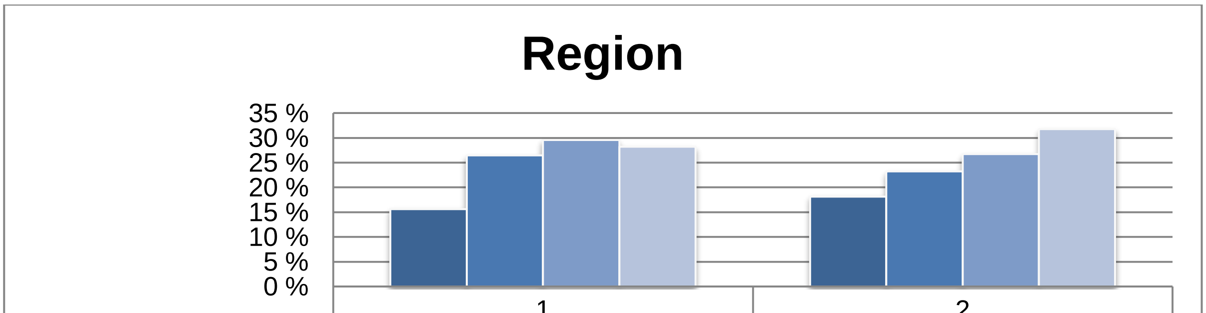


Figure 7.4: Age distribution for the car short distance travel segment

Region

In Figure 7.5 is a comparison between where the respondents of the car short distance travel segment reside and where the Norwegian population as a whole reside (SSB, 2011). The numbering 1 and 2 denotes respondents in the car short segment and the Norwegian population respectively. The regions are defined as follows: Nord and Midt-Norge consists of Finnmark, Troms, Nordland, Nord-Trøndelag and Sør-Trøndelag. Rest of Østlandet consists of Østfold, Vestfold, Buskerud, Telemark, Oppland and Hedmark. Finally, Vest and Sør-Norge consists of Sogn og Fjordane, Hordaland, Rogaland, Vest-Agder, Aust-Agder and Møre og Romsdal.

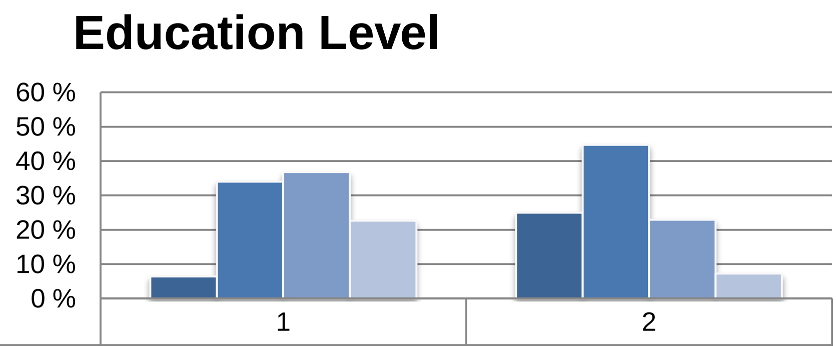


	1	2
Nord and Midt-Norge	15,66 %	18,18 %
Oslo and Akershus	26,51 %	23,27 %
Rest of Østlandet	29,61 %	26,76 %
Vest and Sør-Norge	28,22 %	31,80 %

Figure 7.5: Region of residence for respondents in the car short distance travel segment (1) compared with the Norwegian population (2)

Education Level

The shares for education level for respondents in the car short distance travel segment are given in Figure 7.6 along with the corresponding shares found for the Norwegian population as a whole aged 20 and above (SSB, 2010). The numbering 1 and 2 denotes the respondents in the car short distance travel segment and the Norwegian population respectively. It can be seen that respondents in the car short segment on average have higher education than the Norwegian population as a whole.



	1	2
Grunnskole	6,49 %	25,00 %
Videregående skole	34,03 %	44,77 %
Høgskole/Universitet (less than 4 years)	36,78 %	22,90 %
Universitet (more than 4 years)	22,70 %	7,33 %

Figure 7.6: Education Level for respondents in the car short distance travel segment (1) compared with Norwegian population (2)

A reason for this could be that car users in general might have higher education than people using other modes of transport. Another reason could be that the response rate for the questionnaire was lower for people with low education than for those with high education. This may also be related to the underrepresentation of young respondents in the study. Young people have less education, thus a larger share of young respondents would have increased the share of respondents with low education in the study.

7.2.2 Adding Explanatory Variables

Several explanatory variables were added to the Base Model used in the Norwegian Value of Time Study, to see whether they could increase the explanatory power of the model. A dummy variable for education level was examined, but did not turn out significant. The Base Model was also run with a dummy variable for whether the respondent is working or unemployed. Again, the estimated dummy parameter was not significant. Further, a dummy variable was added to investigate whether VTTS for car users in the short travel segment could be affected by factors making it difficult for them to use public transport. This did not seem to have an impact, as the estimated parameter was not significantly different from zero. After thorough examination, four dummy variables were added to the Base Model.

Respondents from Oslo

Regional dummy variables were included to see whether VTTS varied between different parts of Norway. Four different regions were defined as explained in Section 7.2.1. None of the dummy variables turned out significant and were not included in the Extended Base Model. Rather than using larger parts of the country as dummy variables, a test was performed with cities as regional dummy variables. A reason why this might influence VTTS is that it is stressful to drive in large cities. This might cause increased disutility for car travellers. The Base Model was run separately three times with dummy variables for Bergen, Oslo and Trondheim. The dummy variables for Bergen and Trondheim were found to be insignificant. For Oslo, the dummy variable was found to be significantly different from zero. Thus, the dummy variable for Oslo is added to the Extended Base Model. Figure 7.7 gives some descriptive statistics on respondents residing in Oslo.

Female	Mean Age	Mean Income	Share of respondents
48.79%	45.85	346389	10.66%

Figure 7.7: Descriptive statistics for respondents from Oslo

The share of females from Oslo in the sample is slightly higher than for the study as a whole. Mean age is slightly lower than for rest of the respondents in the study. Mean income is 33827 NOK higher than mean income for the whole study.

Respondents Working Flexible Hours

The Base Model was run with different dummy variables for occupational status. It was found that using a dummy variable for flexible working hours increased the explanatory power of the Base Model. Because of this, a dummy variable for flexible working hours is also added to the Extended Base Model.

Female	Mean Age	Mean Income	Share of respondents
37.95%	45.95	339551	32.42%

Figure 7.8: Descriptive statistics for respondents working flexible hours

Figure 7.8 shows some descriptive statistics for respondents in working flexible hours. Fewer women than men work flexible hours in the car short distance travel segment. Mean age is also slightly lower for respondents working flexible hours, than for the rest of the respondents in the study. Mean income for respondents working flexible hours is 26989 NOK higher than mean income for the car short distance travel segment.

Respondents who do not pay for the Trip themselves

Whether an individual pay for the trip herself, or have someone else pay it for her, may affect VTTS. The Base Model was run with a dummy variable for respondents who did not pay for the trip themselves. The estimated parameter was significantly different from zero, and was added to the Extended Base Model. Figure 7.9 provides some descriptive statistics on respondents who did not pay for the trip themselves.

Female	Mean Age	Mean Income	Share of respondents
37.34%	41.51	316052	7.78%

Figure 7.9: Descriptive statistics for respondents who did not pay for the trip themselves

The share of females is a bit lower than for the rest of the car short segment. Mean age is quite low. This indicates that the share of respondents who are not paying for the trip is higher for younger respondents than for older respondents. Mean income is slightly higher than mean income for the car short segment.

Respondents who do not Walk or Cycle instead of using a Car

A dummy variable was added for respondents who had not walked or cycled to get to an activity during the last year. This can act as a proxy variable for car reliance, and might affect VTTS. The estimated dummy parameter turned out significant, and the dummy variable was included in the Extended Base Model. Figure 7.10 gives some descriptive statistics for respondents who had not walked or cycled to get to an activity during the last year.

The share of females is slightly lower than for the rest of the car short distance travel segment. Mean age is about three years higher. Mean income is slightly lower than mean income for all respondents in the car short distance travel segment.

Female	Mean Age	Mean Income	Share of respondents
39.43%	49.54	309334	33.90%

Figure 7.10: Descriptive statistics for respondents who never walk or cycle

7.2.3 Interpretation of Parameters

Figure 7.11 explains how to interpret the parameters of the Extended Base Model. As can be seen, these parameters are dependent on socio-economic and demographic variables, as well as reference trip characteristics. All parameters listed in the figure were present in the Base Model used for estimation in the Norwegian Value of Time Study, except for parameters written in capital letters, referring to the added explanatory variables.

Parameter Name	**Interpretation**
SNP1, SNP2, SNP3, SNP4	Semi-nonparametric terms
b_age	Age
b_agesq	Age squared divided by 100
b_female	Dummy parameter for female
b_income_miss	Dummy parameter for respondents who has not reported their income
b_log∆T	Elasticity of difference in travel time between alternatives with respect to VTTS
b_logdistance	Elasticity of reference trip travel distance with respect to VTTS
b_logjcost	Elasticity of reference trip travel cost with respect to VTTS
b_logpnetincome	Elasticity of net income with respect to VTTS
b_work	Dummy parameter for travel to work
const	Constant accounting for the individual-specific parameter
sigma	Standard deviation of the individual-specific parameter
eta_c	Dummy parameter for reference-dependent preferences: cost
eta_t	Dummy parameter for reference-dependent preferences: travel time
B_FLEXIBLE	Dummy parameter for respondents with flexible working hours
B_OSLO	Dummy parameter for respondents residing in Oslo
B_NOPAY	Dummy parameter for respondents who have not paid for the trip themselves
B_NOWALK	Dummy parameter for respondents who have not walked or cycled instead of using a car to get to an activity during the last year

Figure 7.11: Explanation of parameters in the Extended Base Model

Biogeme also estimates the scaling parameter μ. This is referred to as the homogeneity parameter in the Biogeme report file. Finally, the variance of the random parameter is given at the end of the report file.

7.2.4 Estimation Results

Figure 7.12 shows the results obtained from the Base Model used in the Norwegian Value of Time Study and the estimated results for the Extended Base Model. The Biogeme report files are found in Figure A.14 and A.15 in the Appendix. 725 Halton draws is used for both models. All parameters that are found to be significant contribute to explaining differences in VTTS among the respondents.

	Base Model		**Extended Base Model**	
Number of parameters	18		22	
Number of observations	24768		24768	
Number of individuals	3097		3097	
Null log-likelihood	-17167.87		-17167.87	
Final log-likelihood	-9599.77		-9589.80	
Rho-square	0.441		0.441	
Adjusted rho-square	0.440		0.440	
	Estimate	t-statistic	Estimate	t-statistic
b_age	0.004	0.41	0.002	0.18
b_agesq	-0.022	-2.13	-0.02	-1.98
b_female	-0.098	-2.64	-0.078	-2.06
b_income_miss	5.30	7.81	5.06	7.38
b_logΔT	0.081	2.99	0.08	3.00
b_logdistance	-0.179	-3.17	-0.152	-2.56
b_logjcost	0.521	9.63	0.488	8.64
b_logpnetincome	0.432	8.06	0.414	7.65
b_work	0.021	0.60	0.017	0.45
const	-6.61	-10.54	-6.64	-10.44
sigma	1.37	6.54	1.28	6.23
eta_c	-0.069	-7.62	-0.069	-7.58
eta_t	0.078	8.14	0.078	8.15
B_FLEXIBLE			0.117	3.11
B_OSLO			0.122	2.20
B_NOPAY			0.203	3.07
B_NOWALK			0.119	2.95

Figure 7.12: Estimation Results from Base Model and Extended Base Model

In addition to the parameters listed in Figure 7.12 are also the SNP parameters. They are found to be significant for both models. Thus, a log-normal distribution for the individual-specific random parameter u is discarded for a generalized distribution for both the Base Model and the Extended Base Model.

The estimated parameters for age are significantly different from zero. Using age as an explanatory variable to explain VTTS does increase the explanatory power of both models. The dummy parameter for female is significant and negative for both models. However, the magnitude of the parameter is slightly smaller in the Extended Base Model. In the Base Model females ceteris paribus have a VTTS that is 9.4% lower than for men. In the Extended Base Model the estimate is 7.5%. The elasticity of differences in travel time between the two alternatives with respect to VTTS is significant for both models. The estimates are identical indicating an elasticity of 0.08. The elasticity of reference trip travel distance with respect to VTTS is significant for both models, but the estimated elasticity is somewhat lower for the Extended Base Model. The elasticity of reference trip cost with respect to VTTS is also significant for both models. There is a positive relationship between the cost of the reference trip and VTTS. The estimated parameter is slightly lower for the Extended Base Model than for the Base Model. The dummy parameter for travel to work is insignificant for both models. The standard deviation of the individual-specific parameter u is lower for the Extended Base Model than for the Base Model. This means that the unobserved heterogeneity in VTTS among respondents is lower for the Extended Base Model than for the Base Model. The reason for this is the inclusion of more explanatory variables to explain observed heterogeneity in the Extended Base Model. Parameters for reference-dependent preferences are estimated to be significant and identical for both models. VTTS in a choice situation is affected by loss aversion.

The parameters for the added explanatory variables in the Extended Base Model are all significantly different from zero. The estimate for the dummy parameter for respondents working flexible hours indicates that these respondents have a VTTS that is 12.4% higher than for other respondents ceteris paribus. The estimate for the dummy parameter for respondents from Oslo predicts that these respondents, conditional on the other explanatory variables, will have a VTTS that is 13% higher than for other respondents. Further, the dummy parameter for respondents not paying for the trip themselves suggest that these respondents have a VTTS that is 22.5% higher than for other respondents ceteris paribus. Finally, the dummy parameter for respondents who has not walked or cycled rather than using a car to get to an activity during the last year indicates that these respondents have a VTTS that is 12.6% higher than for other respondents. The adjusted rho-square is the same for both models. They are equally good in predicting choices made by respondents.

7.2.5 Income Elasticity

Income elasticity in the Extended Base Model for all 3097 respondents is estimated to be 0.414 which is slightly lower than for the Base Model. The robust p-value of 0.00 indicates that it is significantly different from zero. On average, a 1% increase in income will lead to an increase in VTTS of 0.414% for any given respondent in the study. Thus, the addition of extra explanatory variables in the Extended Base Model did not solve the issue of discrepancy between cross-sectional and longitudinal income elasticity of VTTS.

	Income Elasticity	Robust standard error	Robust p-value
Extended Base Model	0.414	0.052	0.00

Figure 7.13: Income Elasticity in the Extended Base Model

7.2.6 Applying the Extended Base Model to Public Transport

The Norwegian Value of Time Study also estimates VTTS for short distance travels with public transport. The Base Model for this segment was run with the additional explanatory variables as proposed in Section 7.2.2 to see whether they could improve the explanatory power of the model. Figure 7.14 gives some descriptive details for the respondents in the public transport short distance travel segment.

Female	Mean Age	Mean Income	Sample Size
61.12%	42.38	293175	571

Figure 7.14: Share of females, mean age, mean income and sample size: Public transport short distance travel segment

Respondents from Oslo

The dummy variable for Oslo turned out significant. A reason for respondents from Oslo to have a different VTTS than other respondents is that the standard of public transport in Oslo is high. This might decrease disutility for travellers in Oslo. The dummy variables for the other added explanatory variables were insignificant. Thus, only a dummy variable for Oslo is added to the Extended Base Model used for the public transport short distance travel segment. The other added variables are discarded. Descriptive data on respondents from Oslo is found in Figure 7.15.

Female	Mean Age	Mean Income	Share of respondents
61.33%	40.53	289780	39.40%

Figure 7.15: Descriptive data for respondents from Oslo: Public transport short distance travel segment

As can be seen from this figure, the respondents from Oslo are quite similar to respondents from other parts of the country. Mean age is slightly lower for respondents from Oslo, as is mean income.

Estimation Results

Figure 7.16 shows the results obtained from the Base Model used in the Norwegian Value of Time Study for the public transport short distance travel segment, as well as results from using the Extended Base Model with a dummy variable for respondents residing in Oslo.

	Base Model for PT		**Extended Base Model for PT**	
Number of parameters	18		19	
Number of observations	4568		4568	
Number of individuals	571		571	
Null log-likelihood	-3166.30		-3166.30	
Final log-likelihood	-1664.85		-1660.84	
Rho-square	0.474		0.475	
Adjusted rho-square	0.469		0.469	
	Estimate	t-statistic	Estimate	t-statistic
b_age	0.013	0.62	0.014	0.69
b_agesq	-0.027	-1.15	-0.029	-1.28
b_female	0.006	0.07	-0.001	-0.02
b_income_miss	7.59	5.45	7.70	5.70
b_logΔT	0.057	1.06	0.05	0.94
b_logdistance	0.042	0.88	0.009	0.19
b_logjcost	0.284	3.03	0.255	2.79
b_logpnetincome	0.617	5.47	0.624	5.70
b_work	-0.027	-0.30	-0.044	-0.51
const	-10.7	-8.17	-10.4	-8.01
sigma	1.46	8.93	1.34	7.10
eta_c	-0.145	-6.61	-0.146	-6.62
eta_t	0.043	2.02	0.043	2.03
B_OSLO			-0.223	-2.87

Figure 7.16: Estimation Results from Base Model and Extended Base Model: Public transport short distance travel segment

The Biogeme report files are found in Figure A.28 and A.29 in the Appendix. 1000 Halton draws is used for both models.

In addition to the parameters listed in the figure above are also the SNP parameters. They are found to be significant for both models. A generalized distribution is used for the individual-specific parameter u rather than the log-normal distribution. The addition of a dummy variable for respondents from Oslo does not change the values of the other parameters very much. Furthermore, those parameters that are insignificant in the Base Model are also insignificant in the Extended Base Model. The same holds for the significant parameters. The estimate of -0.223 for the dummy parameter for Oslo is significant and predicts that VTTS is 20% lower for respondents residing in Oslo than for respondents living in other parts of the country. Sigma in the Extended Base Model is lower than in the Base Model. This indicates that the addition of a dummy variable for respondents from Oslo decreases unobserved utility among respondents. Adjusted Rho-square is equal in both models.

7.3 Income Segmentation

The first alteration of the Extended Base Model for the car short distance travel segment is to divide the respondents into different income groups in order to observe how income elasticity changes with income. The highest after-tax income registered is 584734 NOK. It is important that the span in income for the different income segments is large enough to produce reliable estimates for income elasticity. The following income segments are used: 0-150000, 150001-300000, 300001-450000 and 450001-600000.

7.3.1 Socio-economic and Demographic Data for each Income Segment

In Figure 7.17 is an overview of gender distribution, mean age and mean income for different income segments in the car short segment. Respondents who did not report their incomes are not included.

	Sample Size	Female	Mean Age	Mean Income
Income Segment 1: 0-150000 NOK	238	65.54%	37.32	114369
Income Segment 2: 150001-300000 NOK	1171	53.54%	47.03	246374
Income Segment 3: 300001-450000 NOK	1258	32.35%	47.5	362200
Income Segment 4: 450001-600000 NOK	274	25.91%	47.56	539683

Figure 7.17: Sample sizes, Share of females, mean age and mean income for respondents in each income segment

Gender

There is a predominance of women in the two lower income segments and predominance of men in the two upper income segments. On average, women tend to earn 85% of what men earn (SSB, 2005), so this is not surprising. Although only 43.7% of the sampled respondents are women, the lowest income segment with incomes between 0 and 150000 consists of 65.5% women.

Age

Mean age is quite stable at 47 years for income segment 2, 3 and 4. For the lowest income segment mean age is only 37.3 years. Looking at the age distribution for this income segment also reveals this. This is illustrated in Figure 7.18.

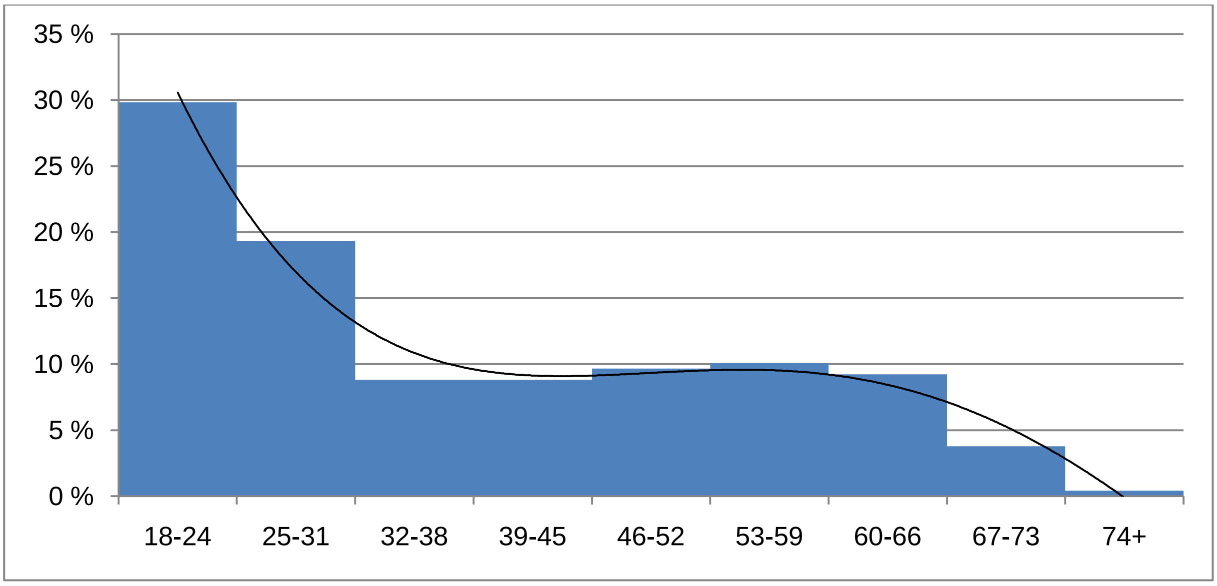
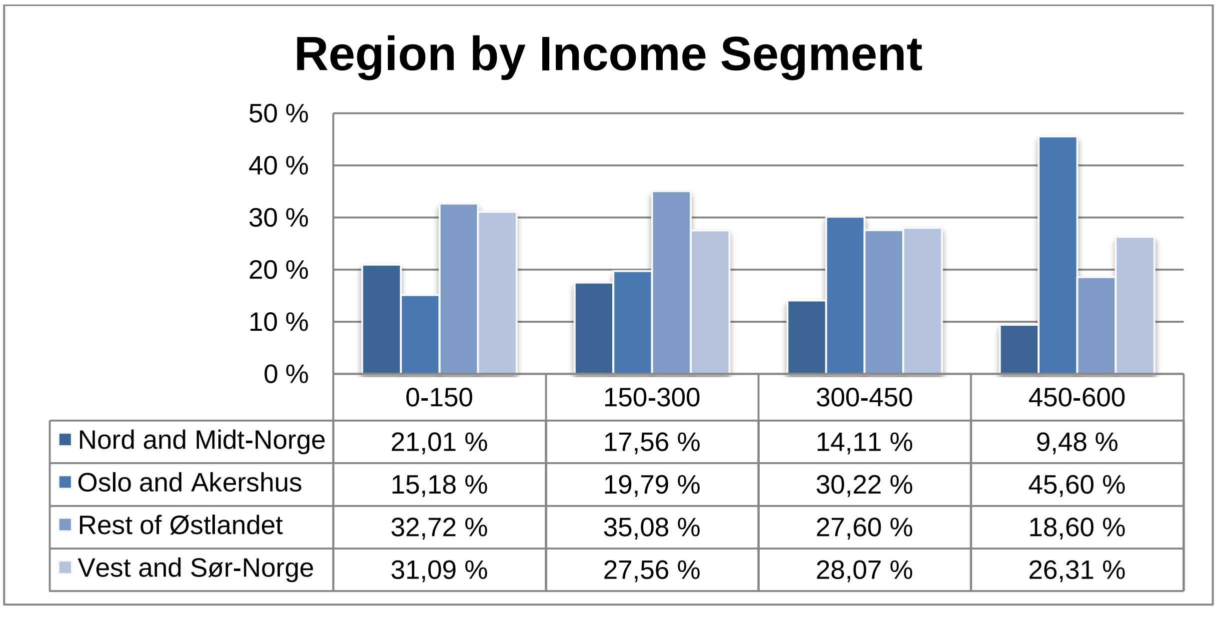


Figure 7.18: Age distribution for respondents with incomes between 0 and 150000

Compared to Figure 7.4, it is easily seen that the lowest income segment is dominated by young respondents. Almost half of the respondents in this income segment are below the age of 30. One reason for this is that 36.1% of the respondents in the lowest income group are students. In none of the three other income segments does the share of students exceed 1% of the respondents. Since there are more female students than male students in Norway (SSB, 2011), this might also be seen as an explaining factor why there are so many females in the lowest income segment.

Region

In Figure 7.19 we see how income and region is related. Respondents living in Oslo and Akershus are heavily overrepresented in the highest income segment and equally underrepresented in the lowest income segment. The opposite holds for respondents from Nord and Midt-Norge. Respondents from the two other regions are quite equally dispersed between the different income segments

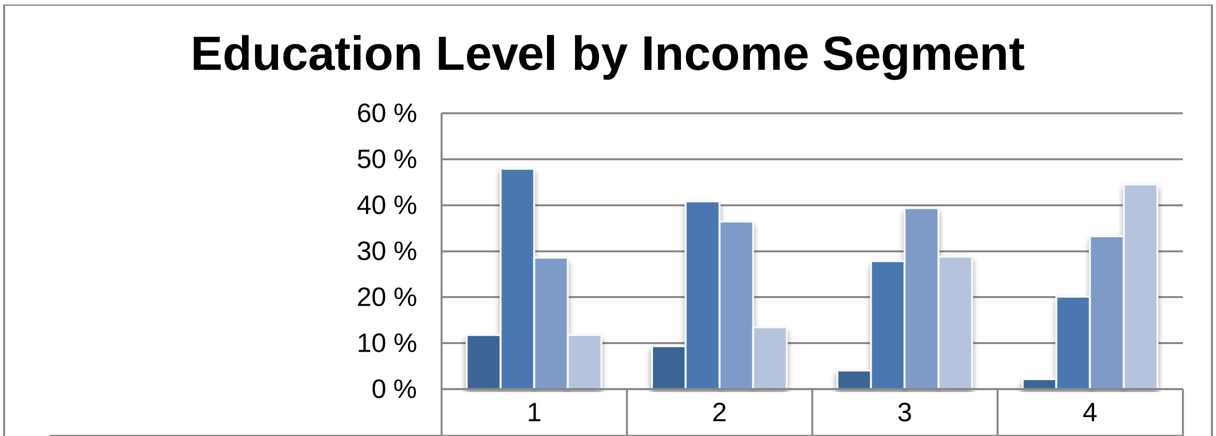


	0-150	150-300	300-450	450-600
Nord and Midt-Norge	21,01 %	17,56 %	14,11 %	9,48 %
Oslo and Akershus	15,18 %	19,79 %	30,22 %	45,60 %
Rest of Østlandet	32,72 %	35,08 %	27,60 %	18,60 %
Vest and Sør-Norge	31,09 %	27,56 %	28,07 %	26,31 %

Figure 7.19: Region and income segment

Education Level

It turns out to be substantial differences in education level for different income segments. Moreover, there is clearly a positive relationship between education and income. This is shown in Figure 7.20. The numbering 1 to 4 denotes income segment.



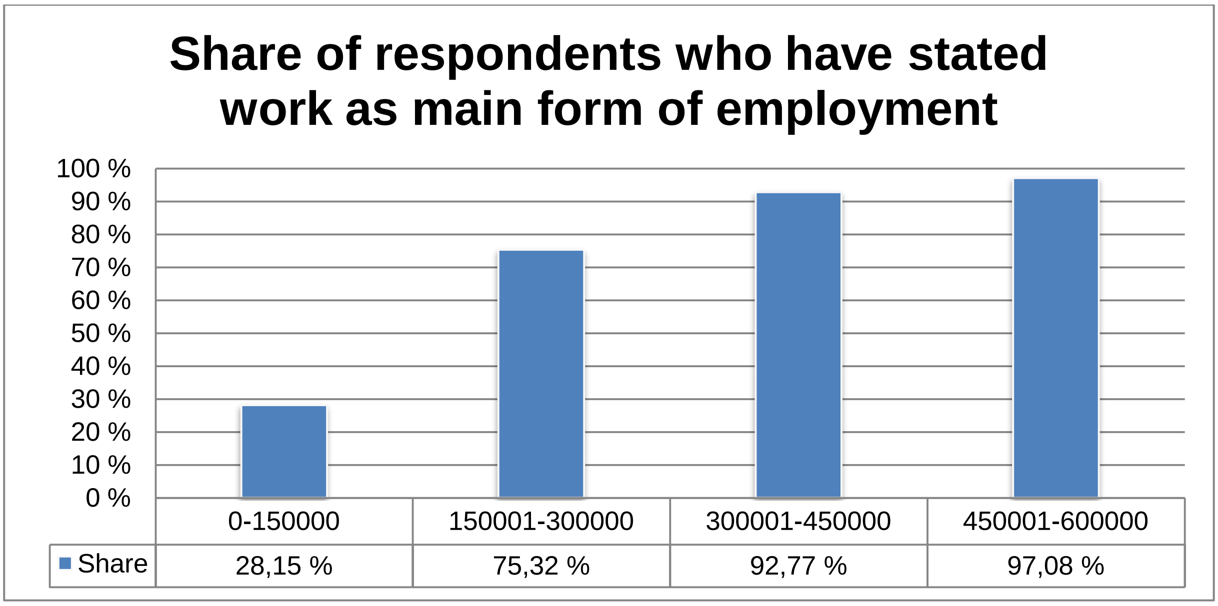
	1	2	3	4
Elementary and Secondary School	11,76 %	9,31 %	4,05 %	2,19 %
High School	47,90 %	40,82 %	27,82 %	20,07 %
College (less than 4 years)	28,57 %	36,46 %	39,35 %	33,21 %
University (more than 4 years)	11,76 %	13,41 %	28,78 %	44,53 %

Figure 7.20: Education level for each income segment

In income segment 1 with incomes ranging from 0 to 150000, there are 40% of respondents with a college (høgskole) or university degree. A reason for this could be that some of these respondents are disabled and receiving social security benefits from the government. Another reason could be that some highly educated respondents in this income segment are retired and receiving pension. In fact, 19.3% of the respondents in the lowest income segment are either pensioners or receiving social security benefits. The high share of students in the lowest income segment can explain the high share of respondents with elementary and secondary school (grunnskole) or high school (videregående skole) as their highest achieved degree.

Occupation

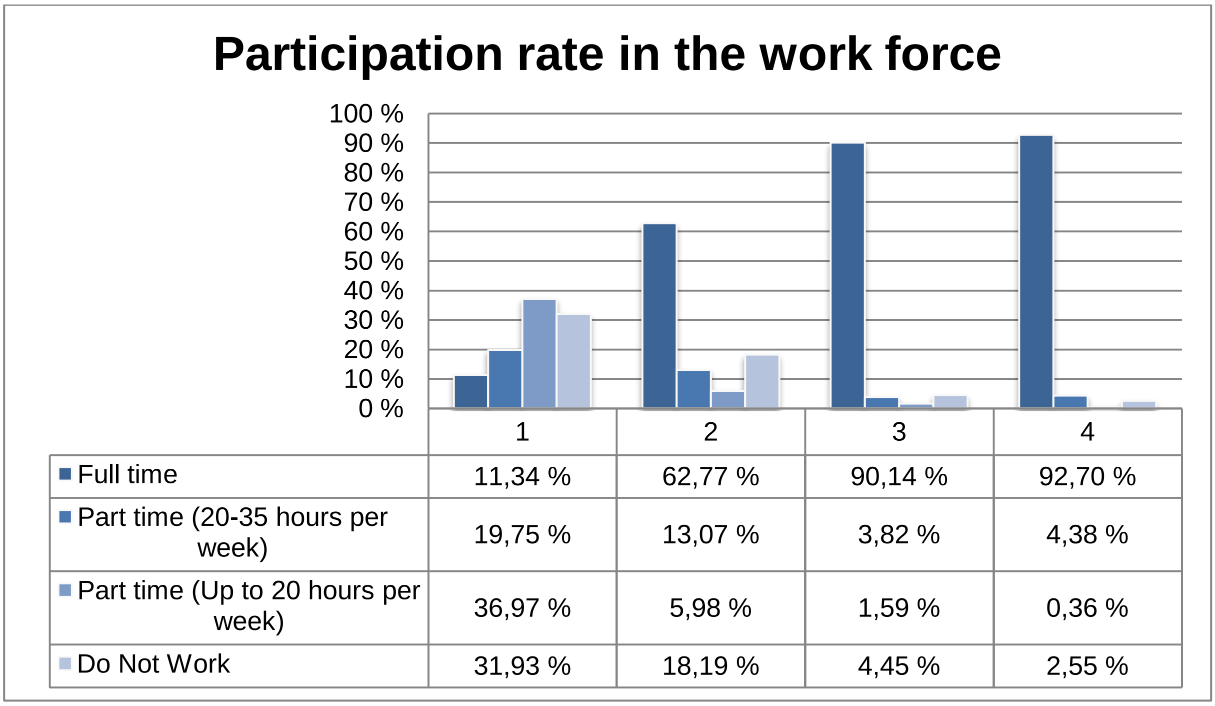
There are also differences for each income segment in terms of share of respondents who have stated work as their main form of employment. This is illustrated in Figure 7.21. Work in this context is defined as either wage labour (inntektsbringende arbeid) or self-employed (eget foretak). Only 28.1% are within one of these categories for the lowest income segment. This is remarkably lower than for any of the three other income segments. As already mentioned, a large share of respondents in the lowest income segment consists of students. It is not common for students to have full time jobs while they study. This could partly explain the low share of workers in the lowest income segment.



	0-150000	150001-300000	300001-450000	450001-600000
Share	28,15 %	75,32 %	92,77 %	97,08 %

Figure 7.21: Shares for work as main form of employment for each income segment

A concept that is related to work as main form of employment is participation rate in the work force. Figure 7.22 gives an overview of participation rates in the work force for each income segment.



	1	2	3	4
Full time	11,34 %	62,77 %	90,14 %	92,70 %
Part time (20-35 hours per week)	19,75 %	13,07 %	3,82 %	4,38 %
Part time (Up to 20 hours per week)	36,97 %	5,98 %	1,59 %	0,36 %
Do Not Work	31,93 %	18,19 %	4,45 %	2,55 %

Figure 7.22: Participation rate in work force for each income segment

Only 11% of the respondents in the lowest income segment work full time. 57% work part time while almost 32% are not working at all. The high share of respondents who do not work is not surprising considering the high share of pensioners and people receiving social security benefits in the lowest income segment. The high share of respondents who are not working could also be related to the high share of students in the lowest income segment. Many students do, however, work part time in order to finance their studies. The lowest income segment also has lower mean age than the other segments. Unemployment is higher for young people than for the rest of the population (SSB, 2010), and could help explaining the low participation rate.

7.3.2 Income Elasticity as a Stepwise Function

Börjesson et al. (2009) use a stepwise function to investigate the relationship between income and income elasticity. As mentioned in Chapter 4, the authors find an increasing relationship between income and income elasticity. Because of this, it is suggested that income elasticity should increase over time because average income in the population is increasing over time. By adopting the approach of Börjesson et al. (2009), it is possible to formulate an Income Segmentation Model allowing for different income elasticity for each income segment.

Börjesson et al. (2009) merge the data from the Swedish value of time study from 1994 and 2007 to perform a joint estimation of the cross-sectional income elasticity. It is not straightforward to conduct the same kind of joint estimation for the Norwegian value of time studies with data collected in 1996 and 2009. This has to do with the design of the experiments. In the Swedish studies, the design of the experiments was identical. In the Norwegian Value of Time Study with data collected in 1996, a randomized fractional factorial design is used (Ramjerdi, 1997). This design is not comparable with the design used in the Norwegian Value of Time Study with data collected in 2009 (Ramjerdi, 2010).

Thus, an attempt to merge the data will not be made in this thesis. The Income Segmentation Model is only formulated for the 2010 study. The following parameter names will be used for describing income elasticity for different income segments: B_INC1, B_INC2, B_INC3 and B_INC4. The numbering 1 to 4 denotes income segment as they were defined earlier in Section 7.3.

Four Income Segments

Respondents with missing income are discarded in the Income Segmentation Model with four income segments. Figure 7.23 shows the result from estimation of the Income Segmentation

Model and the Extended Base Model with missing incomes excluded. The Biogeme report files are found in Figure A.16 and A.17 in the Appendix. 725 Halton draws is used for both models.

	Extended Base Model (without missing incomes)		**Income Segmentation Model (4 segments)**	
Number of parameters	21		24	
Number of observations	23520		23520	
Number of individuals	2941		2941	
Null log-likelihood	-16302.82		-16302.82	
Final log-likelihood	-9139.23		-9134.60	
Rho-square	0.439		0.440	
Adjusted rho-square	0.438		0.438	
	Estimate	t-statistic	Estimate	t-statistic
b_age	0.003	0.25	0.006	0.55
b_agesq	-0.02	-1.84	-0.023	-2.09
b_female	-0.075	-1.92	-0.07	-1.76
b_logΔT	0.065	2.37	0.064	2.32
b_logdistance	-0.147	-2.48	-0.141	-2.39
b_logjcost	0.491	8.65	0.487	8.55
b_logpnetincome	0.423	7.67		
B_INC1			0.000	0.00
B_INC2			0.465	3.24
B_INC3			0.384	2.09
B_INC4			1.24	3.01
b_work	0.019	0.51	0.022	0.59
const	-6.47	-9.92	-1.57	-0.53
sigma	1.27	8.38	1.28	8.16
eta_c	-0.068	-7.39	-0.068	-7.39
eta_t	0.078	7.96	0.078	7.96
B_FLEXIBLE	0.103	2.72	0.095	2.48
B_OSLO	0.092	1.60	0.09	1.56
B_NOPAY	0.171	2.49	0.146	2.10
B_NOWALK	0.112	2.78	0.115	2.86

Figure 7.23: Estimation results for Extended Base Model (without missing incomes) and Income Segmentation Model (4 segments)

The estimated parameters in the Extended Base Model without missing incomes are very similar to those obtained in the Extended Base Model where missing incomes are included. The estimated income elasticity is 0.423, compared to 0.414 obtained in the Extended Base Model with missing incomes included. However, the added regional dummy parameter for

Oslo is no longer significant on a 10% level, with a robust p-value of 0.11. The estimated parameters for age and female are no longer significant on a 5% level, with robust p-values of 0.07 and 0.06.

The only difference between the Extended Base Model without missing incomes and the Income Segmentation Model is that income elasticity is allowed to vary for different income segments. Thus, it is not surprising that the estimated parameters other than income elasticity are almost identical. Final log-likelihood for the Income Segmentation Model is lower than for the Extended Base Model without missing incomes, but the adjusted rho-square is equal for both models.

Figure 7.24 gives the estimated income elasticities for the Income Segmentation Model with four income segments. For the lowest income segment, the estimated income elasticity is estimated to be exactly 0.00. Any additional income for this income segment will not lead to a change in VTTS. For the two middle income groups the estimates are 0.465 and 0.384 respectively. Thus, income elasticity is slightly decreasing between income segment 2 and income segment 3. For the highest income segment income elasticity is estimated to be 1.24. An increase in income of 1% for this income segment will lead to an increase of 1.24% in VTTS.

Income Segment	Income	Income Elasticity	Robust standard error	Robust p-value
1	0-150000	0.00	0.259	1.00
2	150001-300000	0.465	0.144	0.00
3	300001-450000	0.384	0.183	0.04
4	450001-600000	1.24	0.412	0.00

Figure 7.24: Income Elasticity in the integrated model with four income segments

Figure 7.25 shows a graph illustrating the relationship between income and income elasticity. Income is measured in thousands of NOK along the horizontal axis while income elasticity is measured along the vertical axis. The straight line is a linear approximation to the graph. As can be seen from this figure, there seem to be an increasing relationship between income and income elasticity. However, as the estimated income elasticity is lower for income segment 3 than for income segment 2, the relationship is not monotonically increasing.

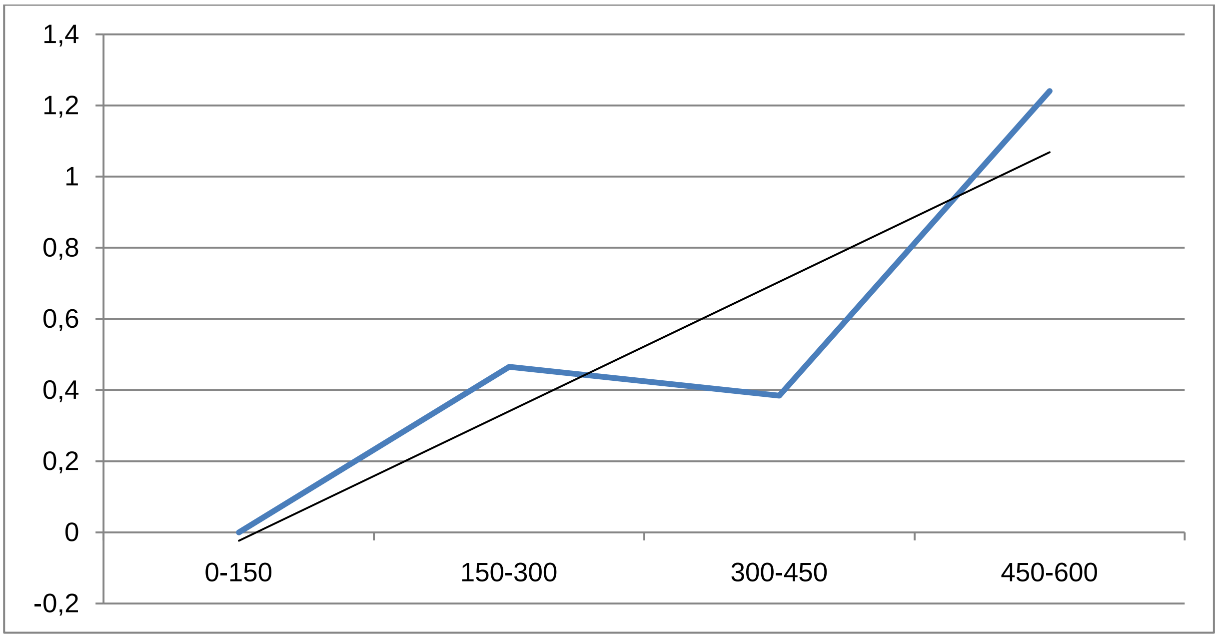


Figure 7.25: How Income Elasticity might vary with income: Four income segments

Three Income Segments

Börjesson et al. (2009) claim that incomes reported by respondents in the lowest income segment are inaccurate. As discussed in Chapter 4, this might lead to incorrect estimates for income elasticity. Section 7.3.1 showed that the composition of the lowest income segment is very different from the other income segments. For example, respondents in the lowest income segment were found to be younger and work less than respondents in other income segments. It is quite likely that these factors might make respondents in this income segment more reliant on other sources of income than their own.

In the study by Börjesson et al. (2009), income segments are formed by which percentile a respondent belongs to in the income distribution. The lowest income segment consists of respondents that earn less than the median income. The middle income includes respondents that are between the 50 and 75 percentile. Finally, the top income segment consists of respondents that are above the 75 percentile in the income distribution.

An attempt was made to replicate the model of Börjesson et al. (2009). However, the income distribution of the Norwegian Value of Time Study did not allow for this type of income segmentation. The income differences for the middle income segment between the 50 and 75 percentile were too small to obtain a reliable estimate for income elasticity. Rather, the same income segments are used as described earlier in this chapter.

Income elasticity is only estimated for income segment 2, 3 and 4 in this model, with incomes spanning from 150000 NOK to 600000 NOK. Converted to percentiles, income segment 2 consists of respondents in the income distribution up to the 43.3 percentile. Income segment 3 consists of respondents in the income distribution between 43.3 and the 90 percentile. Finally, income segment 4 is for incomes above the 90 percentile. For comparison, the Extended Base Model is run with incomes below 150000 NOK excluded. The estimation results are shown in Figure 7.26. The Biogeme report files can be found in Figure A.18 and A.19 in the Appendix. 725 draws is used for both models.

	Extended Base Model with incomes above 150000 NOK		**Income Segmentation Model (3 segments)**	
Number of parameters	21		23	
Number of observations	21617		21617	
Number of individuals	2703		2703	
Null log-likelihood	-14983.76		-14983.76	
Final log-likelihood	-8452.77		-8450.69	
Rho-square	0.436		0.436	
Adjusted rho-square	0.434		0.434	
	Estimate	t-statistic	Estimate	t-statistic
b_age	0.002	0.13	0.003	0.24
b_agesq	-0.018	-1.54	-0.019	-1.66
b_female	-0.041	-0.98	-0.047	-1.13
b_log∆T	0.052	1.83	0.053	1.86
b_logdistance	-0.102	-1.59	-0.101	-1.59
b_logjcost	0.458	7.53	0.457	7.53
b_logpnetincome	0.543	6.84		
B_INC2			0.448	2.50
B_INC3			0.422	2.26
B_INC4			1.25	3.01
b_work	0.012	0.30	0.015	0.38
const	-8.09	-8.20	-6.92	-3.07
sigma	1.37	6.82	1.37	7.23
eta_c	-0.066	-6.87	-0.066	-6.87
eta_t	0.077	7.59	0.078	7.58
B_FLEXIBLE	0.105	2.65	0.102	2.58
B_OSLO	0.105	1.73	0.107	1.77
B_NOPAY	0.124	1.63	0.124	1.64
B_NOWALK	0.111	2.58	0.11	2.56

Figure 7.26: Estimation results for Extended Base Model with incomes above 150000 NOK (without missing incomes) and Income Segmentation Model (3 segments)

The estimated parameters for the Extended Base Model with incomes above 150000 NOK are somewhat different than for the Extended Base Model where all incomes are included. The parameters for age and female are not significant in the Extended Base Model with incomes above 150000 NOK. Thus, age and female seem to be more important explanatory variables for respondents in the lowest income segment than for other respondents. The elasticity of travel distance with respect to VTTS is not significant either. All the added explanatory variables are still significant in the Extended Base Model with incomes above 150000 NOK. The estimated parameters are quite similar except for the parameter referring to respondents who did not pay for the trip themselves. The predicted effect on VTTS for this variable is only 13.2%, compared to 22.5% in the Extended Base Model where all incomes are included. This indicates that the value of this parameter is larger for the lowest income segment than for incomes above 150000 NOK. Adjusted rho-square is equal for both models.

Income elasticity in the Extended Base Model with incomes above 150000 NOK is 0.543, as shown in Figure 7.27. This is higher than 0.414 found in the Extended Base Model, but much lower than the longitudinal income elasticity of 0.9 found by Wardman (2009). Thus, excluding the lowest income segment does not solve the issue of discrepancy between cross-sectional and longitudinal income elasticity.

	Income Elasticity	Robust standard error	Robust p-value
Extended Base Model with incomes above 150000 NOK	0.543	0.073	0.00

Figure 7.27: Income Elasticity for the Extended Base Model with incomes above 150000 NOK

Income elasticities in the Income Segmentation Model with three segments are quite equal to the estimates obtained in the Income Segmentation Model with four segments. The estimates are given in Figure 7.28. Income elasticity is still lower for income segment 3 than for income segment 2, but the difference between the two estimates is smaller.

Income Segment	Income	Income Elasticity	Robust standard error	Robust p-value
2	150001-300000	0.448	0.180	0.01
3	300001-450000	0.422	0.187	0.02
4	450001-600000	1.25	0.417	0.00

Figure 7.28: Income Elasticity for the Income Segmentation Model with three income segments

7.4 Segmentation by Gender and Age

As the discussion in Section 7.3.2 shows, income elasticity seems to be an increasing function of income. However, income elasticity might also be related to other characteristics of the respondents. This Section presents the results of segmenting the Extended Base Model by gender and by age.

7.4.1 Gender

Figure 7.29 gives the estimation results for the Extended Base Model when the model is run separately for men and women. The Biogeme report files can be found in Figure A.20 and A.21 in the Appendix. 500 draws is used for both models. For obvious reasons the dummy parameter for female is excluded.

	Extended Base Model: Men		**Extended Base Model: Women**	
Number of parameters	21		21	
Number of observations	13932		10836	
Number of individuals	1742		1355	
Null log-likelihood	-9656.93		-7510.94	
Final log-likelihood	-5463.65		-4113.41	
Rho-square	0.434		0.452	
Adjusted rho-square	0.432		0.450	
	Estimate	t-statistic	Estimate	t-statistic
b_age	-0.025	-1.74	0.034	1.93
b_agesq	0.006	0.43	-0.052	-2.65
b_income_miss	6.20	6.27	4.00	4.13
b_logΔT	0.03	0.83	0.15	3.71
b_logdistance	-0.112	-1.53	-0.244	-2.52
b_logjcost	0.478	6.91	0.524	5.90
b_logpnetincome	0.498	6.41	0.33	4.25
b_work	0.000	0.01	0.022	0.40
const	-6.85	-7.86	-6.28	-7.09
sigma	1.45	8.17	1.41	6.06
eta_c	-0.067	-5.68	-0.069	-4.97
eta_t	0.079	6.01	0.078	5.52
B_FLEXIBLE	0.147	3.05	0.06	1.02
B_OSLO	0.114	1.45	0.101	1.22
B_NOPAY	0.253	3.03	0.095	0.85
B_NOWALK	0.148	2.89	0.066	1.07

Figure 7.29: Estimation results for Extended Base Model segmented by gender

Neither of the added dummy parameters in the Extended Base Model is significant for women. For men, all but the regional dummy parameter for Oslo are significantly different from zero. The estimates predict ceteris paribus that men who are working flexible hours have a VTTS that is 15.8% higher than for other men. Men who did not pay for the trip have a VTTS that is 28.8% higher than for other men, conditional on the other explanatory variables. Finally, men who has not walked or cycled instead of using a car to get to an activity during the last year have a VTTS that is 16% higher than for other men.

In addition to the parameters in the figure above are also the SNP parameters. They were found to be significant for both models. Thus, a log-normal distribution for the individual-specific random parameter u is discarded in favour of a generalized distribution for both models. The parameter for age is significantly different from zero for both men and women, indicating that VTTS varies with age regardless of gender. The elasticity of difference in travel time between the two alternatives with respect to VTTS is insignificant for men. For women it is significant and estimated to be 0.15. Thus, the significant estimate of 0.08 found in the Extended Base Model for both genders seem to be driven mainly by female respondents.

The elasticity of reference trip travel distance with respect to VTTS is significant for women, with an estimate of -0.244. The estimate for men is insignificantly different from zero. This indicates that elasticity of reference trip travel distance is a better explanatory variable to explain VTTS for women than for men. The elasticity of reference trip cost with respect to VTTS is significant for both models. There is a positive relationship between the cost of the reference trip and VTTS. The estimates indicate an elasticity of about 0.5 for both men and women. The dummy parameter for travel to work is insignificant for both genders. The standard deviation of the individual-specific parameter u is almost the same in both models. Parameters for reference-dependent preferences are estimated to be significant for both men and women. VTTS in a choice situation is affected by loss aversion.

Income Elasticity

Income elasticity is estimated to be higher for men than for women. Thus, VTTS increases at a higher rate with income for men than for women. On average, men in the sample earn 55084 NOK more than women. Thus, it is not too surprising that men have higher income elasticity than women, considering the results obtained in Section 7.3. The estimated income elasticity of VTTS of 0.498 for men is, however, much lower than the longitudinal income elasticity found by Wardman (2009).

	Income Elasticity	Robust standard error	Robust p-value	Mean Income
Men	0.498	0.078	0.00	336180
Women	0.33	0.078	0.00	281096

Figure 7.30: Gender and Income Elasticity

7.4.2 Age

The Extended Base Model is segmented into six different age groups to investigate how income elasticity depends on age. The model is estimated separately for each age group. The results are given in Figure 7.31.

	18-31	**32-38**	**39-45**	**46-52**	**53-59**	**60+**
Number of parameters	20	20	20	20	20	20
Number of observations	4129	3088	4856	4160	3703	4832
Number of individuals	517	386	607	520	463	604
Null log-likelihood	-2862.01	-2140.44	-3365.92	-2883.49	-2566.72	-3349.29
Final log-likelihood	-1567.35	-1235.62	-1891.36	-1600.69	-1457.69	-1736.10
Rho-square	0.452	0.423	0.438	0.445	0.432	0.482
Adjusted rho-square	0.445	0.413	0.432	0.438	0.424	0.476
	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate
b_female	-0.311	-0.166	0.157	(-0.037)	(-0.159)	(-0.029)
b_income_miss	3.73	4.07	3.33	8.30	4.84	8.09
b_logΔT	0.182	(-0.042)	(0.024)	0.214	(0.015)	(0.064)
b_logdistance	(-0.151)	(-0.183)	(-0.023)	-0.446	(0.101)	(0.002)
b_logjcost	0.388	0.532	0.456	0.683	0.366	0.372
b_logpnetincome	0.301	0.386	0.271	0.647	0.434	0.629
b_work	(0.048)	(-0.058)	(-0.076)	0.146	(0.022)	(0.09)
const	-5.23	-6.16	-5.07	-10.0	-7.77	-9.58
sigma	0.984	0.915	1.57	1.78	2.41	1.73
eta_c	-0.051	(-0.036)	-0.076	-0.044	-0.101	-0.103
eta_t	0.064	(0.034)	0.047	0.082	0.119	0.134
B_FLEXIBLE	(0.108)	0.152	0.269	(-0.057)	(0.009)	(0.152)
B_OSLO	(0.098)	(0.047)	0.242	(0.065)	0.377	(-0.05)
B_NOPAY	0.339	(-0.107)	(0.052)	0.402	(-0.005)	0.495
B_NOWALK	(0.018)	0.163	0.234	(0.094)	(-0.03)	0.17

Figure 7.31: Estimation results for age segmentation

Estimates that are written in parentheses are not significant. All other estimates are significant on a 10% level. The Biogeme report files are found in the Appendix in Figure A.22-A.27. 500 Halton draws is used for each model. The parameters for age are excluded in this model.

In addition to the parameters in the figure are also the SNP parameters. These are found to be significant for all age groups except 18-31. For this age group, the log-normal distribution of u is accepted. For the other age groups, the generalized distribution of u is preferred over the log-normal distribution. The dummy parameter for female is significant and negative for age group 18-31 and 32-38, as it is in the Extended Base Model. For the age group 18-31, women have a VTTS that is 26.7% lower than for men ceteris paribus. Thus, it seems that the estimated dummy parameter for female found in the Extended Base Model for all age groups is driven mainly by young respondents. For the age group 39-45, the parameter is significant and positive, which contradicts the Extended Base Model. The elasticity of differences in travel time between the two alternatives with respect to VTTS is significant for age groups 18-31 and 46-52. For the other age groups it is insignificant.

The elasticity of reference trip travel distance is insignificant for all age groups except 46-52. The elasticity of reference trip travel cost is significant and positive for all age groups. VTTS increases with the cost of the trip. The dummy parameter for travel to work is significant for the age group 46-52 predicting these travels yields a VTTS that is 15.7% higher than for other travel purposes. For the other age groups the parameter is insignificantly different from zero. The standard deviation of the individual-specific parameter u is significant for all age groups. The estimate for this parameter is higher for the upper age groups than for the lower age groups. This indicates that the unobserved part of VTTS is larger for old respondents than for young respondents. Parameters for loss aversion are significant for all age groups except 32-38. For the two upper age groups 53-59 and 60+ the estimated loss aversion is higher than for the younger age groups.

The added dummy parameter for respondents with flexible working hours is significant and positive for age groups 32-38 and 39-45. For the other age groups it is insignificant. The regional dummy parameter for Oslo is positive and significantly different from zero for age groups 39-45 and 53-59. Respondents who did not pay for the trip themselves are estimated to have a higher VTTS for age groups 18-31, 46-52 and 60+. For the other age groups the parameter is insignificant. Finally, the dummy parameter for respondents who has not walked or cycled to get to an activity during the last year is significant and positive for age groups 32-38, 39-45 and 60+.

Income Elasticity

The relationship between age and income elasticity is given in Figure 7.32. Income elasticity is estimated to be highest for the age groups 46-52 and 60+. On the other hand, it is lowest for age groups 18-31 and 39-45. None of the estimated income elasticities are close to the longitudinal income elasticity of 0.9 found by Wardman (2009).

	Income Elasticity	Robust standard error	Robust p-value
18-31	0.301	0.100	0.00
32-38	0.386	0.151	0.01
39-45	0.271	0.134	0.04
46-52	0.647	0.149	0.00
53-59	0.434	0.157	0.01
60+	0.629	0.152	0.00

Figure 7.32: Age and Income Elasticity

Figure 7.33 provides a graphical presentation of the relationship between age, income and income elasticity. For each age group mean income in NOK is measured on the left vertical axis and income elasticity is measured on the right vertical axis. The straight line is a linear approximation to how income elasticity varies between age groups.

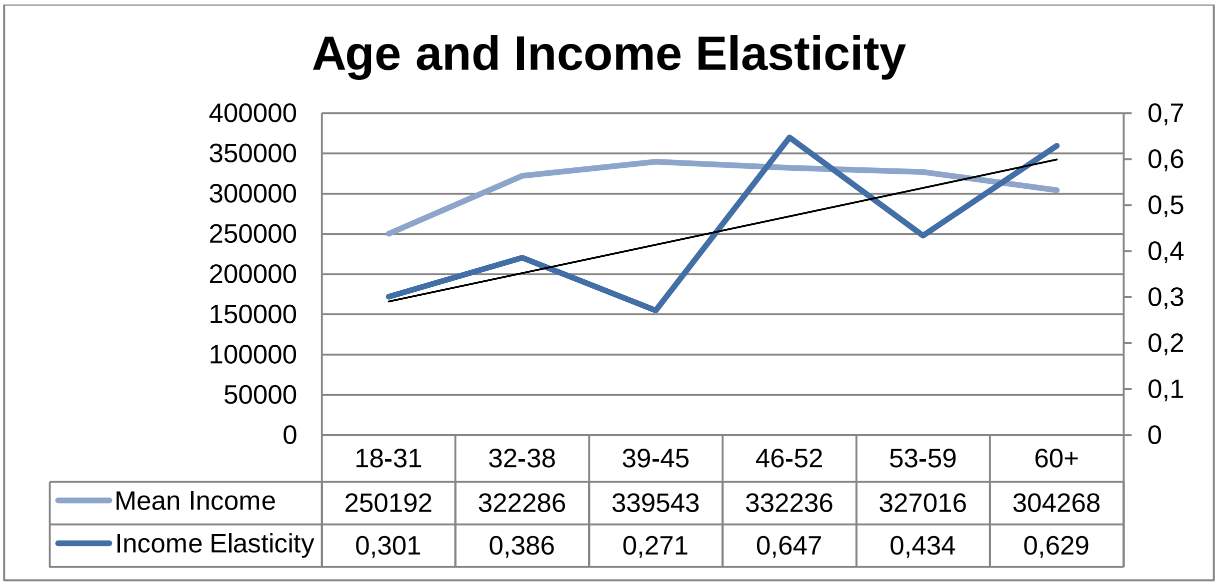


Figure 7.33: Age, income elasticity and income

It is not surprising that income elasticity is low for the age group 18-31, considering that this age group has a lower mean income than all other age groups. In Section 7.3 it was found that there most likely is a positive relationship between income and income elasticity. Since mean income is quite stable for the other age groups, one should expect that income elasticity also should be quite stable. However, it is not possible to conclude that this is the case. Income elasticity is fluctuating between 0.271 and 0.647 even though mean income only varies from 304268 NOK to 339543 NOK. In fact, the age group with the highest mean income has the lowest income elasticity.

While there might not be a relationship between income and income elasticity for different age groups, there could be a relationship between income elasticity and age. The linear approximation seems to indicate that income elasticity is in fact increasing with age. Thus, it can be argued that income elasticity will change over time if the age distribution of the population changes.

7.5 Summary

This chapter has presented the estimation result of numerous models. The Extended Base Model for the car short distance travel segment consisted of four new explanatory variables compared with the Base Model used in the Norwegian Value of Time Study. It was estimated that respondents from Oslo have a VTTS that is 13% higher than for respondents residing elsewhere. Further, a 22.5% higher VTTS is found for those who do not pay for the trip themselves. Respondents who work flexible hours are estimated to have a VTTS that is 12.4% than the rest of the sample. Finally, the dummy parameter for respondents who have not walked or cycled to get to an activity, rather than using a car during the last year, indicates that these respondents have a VTTS that is 12.6% higher than other respondents ceteris paribus. The estimated income elasticity for the Extended Base Model was 0.414 which is slightly lower than 0.432 found in the Base Model. Thus, the addition of new explanatory variables did not solve the issue of discrepancy between cross-sectional and longitudinal income elasticity of VTTS. The Extended Base Model was also run for the public transport short distance travel segment. However, only one of the added dummy variables turned out significant. It is predicted that respondents residing in Oslo have a VTTS that is 20% lower than for respondents residing in other parts of the country.

The Extended Base Model for the car short distance travel segment was used to investigate how income elasticity of VTTS varied between different segments of data. The Income Segmentation Model showed that it is quite likely that income elasticity is an increasing function of income. However, the results were not completely convincing since income elasticity was in fact decreasing between income segment 2 and income segment 3. Only for the highest income segment was income elasticity found to be larger than unity. Following the approach of Börjesson et al. (2009), the Extended Base Model as well as the Income Segmentation Model was estimated with the lowest income segment excluded. Income elasticity increased to 0.543 for the Extended Base Model. This is still much lower than the longitudinal income elasticity of 0.9 found by Wardman (2009). For the Income Segmentation Model, the results were quite equal to those obtained in the same model with all incomes included.

Segmenting the data set by gender produced estimated income elasticities of 0.498 and 0.33 for men and women respectively, indicating that VTTS increases at a higher rate with income for men than for women. The discrepancy of income elasticity between men and women could be related to income as women in the sample have a lower mean income than men. Neither of the added explanatory variables in the Extended Base Model proved significant for female respondents. For men, all but one of the added explanatory variables was significant. Finally, segmenting the data set by age groups produced income elasticities varying between 0.271 and 0.647. There seemed to be an increasing relationship between income elasticity and age. However, neither age group had an income elasticity of VTTS that was close to the longitudinal income elasticity of 0.9 found by Wardman (2009).

Conclusion

The focus of this thesis has been to explain why the cross-sectional income elasticity of VTTS is found to be lower than the longitudinal income elasticity of VTTS. By using the econometric framework by Fosgerau et al. (2007), an Extended Base Model was formulated for data from the Norwegian Value of Time Study. The Extended Base Model included four new variables in addition to those in the Base Model used in the Norwegian Value of Time Study. All the added variables were found to be significant. Income elasticity was estimated to be slightly lower for the Extended Base Model than for the Base Model.

By segmenting the respondents by income it was found that there most likely is a positive relationship between income and income elasticity.

The positive relationship between income and income elasticity is in line with the results found by Börjesson et al. (2009). Excluding the respondents in the lowest income segment did increase income elasticity. However, it did not fully explain the discrepancy between cross-sectional and longitudinal income elasticity. The reason for exclusion was that the reported income of the respondents in the lowest income segment is most likely inaccurate due to transfers or incomes other than wage income. However, it is questionable whether excluding the lowest income segment from estimation is correct. Income elasticity for the lowest income segment is estimated to be exactly zero. If one assumes that respondents in the lowest income segment actually had higher incomes than they had reported, and income elasticity is increasing with income, then the income elasticity of this segment should have been larger than zero.

Following the approach of Börjesson et al. (2009), the Extended Base Model as well as the Income Segmentation Model was estimated with the lowest income segment excluded. Income elasticity increased from 0.414 to 0.543 for the Extended Base Model. This is still much lower than the longitudinal income elasticity of 0.9 found by Wardman (2009) and an income elasticity of close to 1.0 based on a comparison of results from the Norwegian studies in 1996 and 2009. The exclusion of the lowest income segment did not change income elasticities for the other three income segments in the Income Segmentation Model.

It is of great importance to estimate the cross-sectional income elasticities for the corresponding income segments in the Norwegian Value of Time Study from 1996. If income elasticity stay stable for each income segment it can be concluded that the longitudinal income elasticity for each income segment will be 1.0. The comparison of VTTS in the Norwegian Value of Time Study of 1996 and 2009 results in a longitudinal income elasticity of close to 1.0. Hence, most likely the income elasticity of VTTS for different income segments in the 1996 study are similar in size to the corresponding values in the 2009 study. If income elasticity for each income segment has stayed stable, it is also possible to infer that the average cross-sectional income elasticity has increased over time because of changes in the income distribution and increase in average income. Thus, another point of interest is how the income distribution and average income elasticity has changed between the 1996 and the 2009 study. This is a subject of further research.

Respondents in the Norwegian Value of Time Study were also segmented by gender and age. It was found that men have a higher income elasticity of VTTS than women. Further, none of the added explanatory variables in the Extended Base Model were significant for women, while all except one were significant for men. This indicates that different explanatory variables should be used for men and women to explain heterogeneity in VTTS. Segmentation by age showed that there might be a relationship between age and income elasticity. Hence income elasticity could be an increasing function of age. If the age distribution of a population changes over time, causing mean age to increase, this could in effect result in an increased cross-sectional income elasticity of VTTS. For aging populations the implication would be less discrepancy between the cross-sectional and longitudinal income elasticity. A recommendation for further study is to see whether the pattern of increasing income elasticity with age is present in other value of time studies as well.

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Appendix

Common questionnaire used to collect data on respondents

- Age

Aller først:

Hvilket år er du født? *(fire sifre)*

Figure A.1: Age

- Gender

Ditt kjønn:

- Mann
- Kvinne

Figure A.2: Gender

- Education

Hva er din høyeste allmennutdannelse?

- Grunnskole (folkeskole/barneskole og eventuell ungdomsskole)
- Videregående skole (3 år utover grunnskole)
- Høgskole/universitetsutdannelse (inntil 4 år etter videregående)
- Universitetsutdannelse (mer enn 4 års utdannelse etter videregående)

Figure A.3: Education

- Occupation

Hva er din hovedsaklige sysselsetting?

- Inntektsbringende arbeid
- Eget foretak
- Elev, student
- Hjemmearbeidende
- Arbeidsledig, på tiltak
- Pensjonist, trygdet
- Foreldrepermisjon
- Vernepliktig
- Annet

Figure A.4: Occupation

- Respondents are asked whether they work part time or full time.

Er du yrkesaktiv på heltid eller deltid?

- Heltid (35 timer pr. uke eller mer)
- Deltid (under 35 timer pr. uke, men over 20 timer pr. uke)
- Deltid (20 timer eller mindre pr. uke)
- Arbeider ikke

Figure A.5: Hours of work per week

- Respondents are asked whether they work regular hours, work flexible hours or shift.

Er din arbeidstid på en normal arbeidsdag fast, fleksibel eller arbeider du skift?

- Fast
- Fleksibel
- Skiftarbeid

Figure A.6: Regular working hours, flexible working hours or shift

- Region

Hvilken kommune bor du i?

A14

	Fylke - Kommune
A14_r1_c1	

Figure A.7: Place of residence

- Respondents are asked whether they have walked or cycled instead of using car in order to get to an activity during the last year.

Vi vil nå gi deg noen spørsmål knyttet til hvor ofte du sykler eller går, **i stedet for å bruke bil eller offentlige transportmidler**, for å komme til en aktivitet. Vi er her ikke interessert i sykling eller gange som er knyttet til mosjon/rekreasjon.

Har du i løpet av det siste året syklet eller gått
- til/fra arbeid/skole,
- i forbindelse med legebesøk, innkjøpsreise eller lignende,
- for å besøke familie/venner, eller til ulike arrangementer, eller
- i forbindelse med annen reise (ikke sykkelturer og turgåing som kun er for mosjon/rekreasjon)?

- Ja
- Nei

Figure A.8: Walk or cycle instead of car

- Personal pre-tax income. For use in the data analysis taxes are deducted from pre-tax income such that after-tax income is used.

Hvor stor er din egen årssinntekt før skatt?

- Under 100 000 kr/år
- 100 001- 200 000 kr/år
- 200 001- 300 000 kr/år
- 300 001- 400 000 kr/år
- 400 001- 500 000 kr/år
- 500 001- 600 000 kr/år
- 600 001 - 700 000 kr/år
- 700 001 – 800 000 kr/år
- Over 800 000 kr/år
- Vet ikke
- Ønsker ikke å svare

Figure A.9: Pre-tax income

- Respondents are asked to write a travel diary describing some characteristics of trips they recently have taken.

Reisedagboken

I tabellen ("Reisedagboken") under skal du velge startsted, hensikt med reisen og hovedtransportmiddel per reise. Med hovedtransportmiddel menes transportmiddel du brukte på den lengste delen (i kilometer) av reisen. Du skal også anslå reiselengden og reisetiden, per reise, på hovedtransportmid eksempel, tenk deg at du på reise til arbeid benytter både buss og T-bane, men at den lengste delen av reisen foregår med T-bane (i km). Da skal du og ca antall km på den delen av reisen der du benytter T-bane.

Hvis du har gjennomført flere en fem reiser den dagen, velg ut fem av dem som du fyller ut i skjemaet nedenfor.

Lykke til med utfyllningen!

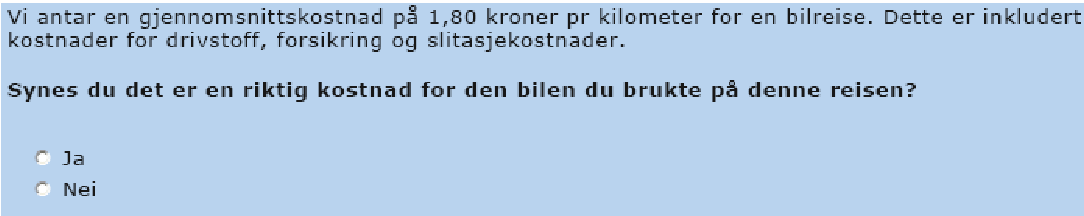
Dersom du synes det er vanskelig å svare, skriv inn det du tror eller gjetter er omtrent riktig. Husk at 1 mil = 10 km. Du må fylle ut alle rubrikkene for å komme vi reisetid null timer/minutter vennligst velg alternativet "0" i listen.

	Startsted	Reisehensikt	Hoved - transportmiddel	Reiselengde (Kilometer)	Reisetid (Timer)
Reise 1	KSRDS_r1_c1	KSRDS_r1_c2	KSRDS_r1_c3	KSRDS_r1_c4 km	KSRDS_r1_c5
Reise 2	KSRDS_r2_c1	KSRDS_r2_c2	KSRDS_r2_c3	KSRDS_r2_c4 km	KSRDS_r2_c5
Reise 3	KSRDS_r3_c1	KSRDS_r3_c2	KSRDS_r3_c3	KSRDS_r3_c4 km	KSRDS_r3_c5
Reise 4	KSRDS_r4_c1	KSRDS_r4_c2	KSRDS_r4_c3	KSRDS_r4_c4 km	KSRDS_r4_c5
Reise 5	KSRDS_r5_c1	KSRDS_r5_c2	KSRDS_r5_c3	KSRDS_r5_c4 km	KSRDS_r5_c5

Neste

Figure A.10: Travel diary

- Respondents are asked whether they think a cost of travelling by car of 1.80 NOK per kilometer is reasonable.



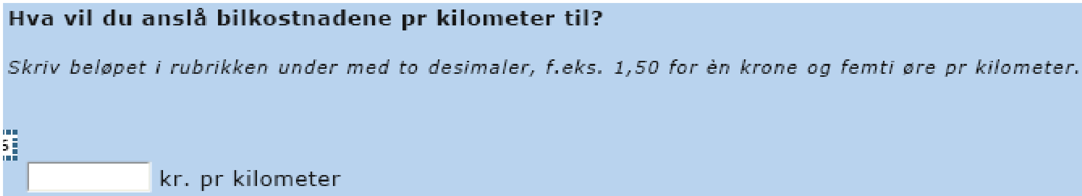
Vi antar en gjennomsnittskostnad på 1,80 kroner pr kilometer for en bilreise. Dette er inkludert kostnader for drivstoff, forsikring og slitasjekostnader.

Synes du det er en riktig kostnad for den bilen du brukte på denne reisen?

- Ja
- Nei

Figure A.11: Cost per kilometer

- Respondents who answer no to the above questions are given a follow up question where they state what they perceive the correct cost to be.



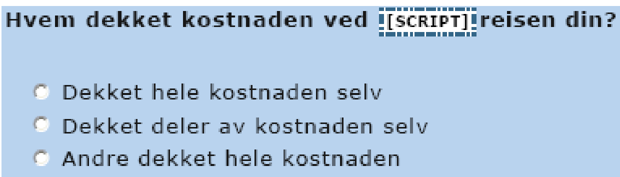
Hva vil du anslå bilkostnadene pr kilometer til?

Skriv beløpet i rubrikken under med to desimaler, f.eks. 1,50 for èn krone og femti øre pr kilometer.

kr. pr kilometer

Figure A.12: Cost per kilometer

- Respondents were asked whether they paid for the trip themselves.



Hvem dekket kostnaden ved [SCRIPT] reisen din?

- Dekket hele kostnaden selv
- Dekket deler av kostnaden selv
- Andre dekket hele kostnaden

Figure A.13: Who paid for the trip

Biogeme Report Files from Estimation

Figure A.14: Results for Base Model used in the Norwegian Value of Time Study (Ramjerdi, 2010) for car short distance travel segment

```
                        Model:  Mixed Multinomial Logit for panel data
        Number of Halton draws: 725
Number of estimated parameters: 18
        Number of observations: 24768
         Number of individuals: 3097
           Null log-likelihood: -17167.869
            Cte log-likelihood: -15611.938
           Init log-likelihood: -9603.890
          Final log-likelihood: -9599.765
         Likelihood ratio test: 15136.208
                    Rho-square: 0.441
           Adjusted rho-square: 0.440
           Final gradient norm: +4.699e-02
                    Diagnostic: Convergence reached...
                    Iterations: 16
                      Run time: 01h 29:15
           Variance-covariance: from finite difference hessian
                   Sample file: Car_short_final_w.dat

Utility parameters
******************
Name            Value   Std err   t-test p-val   Rob. std err Rob. t-test Rob. p-val
----            -----   -------   ------ -----   ------------ ----------- ----------
SNP1            -0.0700 0.0762    -0.92  0.36  * 0.0785       -0.89       0.37       *
SNP2            -0.266  0.0645    -4.12  0.00    0.0734       -3.62       0.00
SNP3            -0.0184 0.0615    -0.30  0.76  * 0.0622       -0.30       0.77       *
SNP4            0.163   0.0360    4.52   0.00    0.0381       4.28        0.00
b_age           0.00403 0.00905   0.45   0.66  * 0.00971      0.41        0.68       *
b_agesq         -0.0217 0.00951   -2.29  0.02    0.0102       -2.13       0.03
b_female        -0.0983 0.0371    -2.65  0.01    0.0373       -2.64       0.01
b_income_miss   5.30    0.651     8.14   0.00    0.678        7.81        0.00
b_logΔT         0.0805  0.0246    3.27   0.00    0.0269       2.99        0.00
b_logdistance   -0.179  0.0540    -3.32  0.00    0.0565       -3.17       0.00
b_logjcost      0.521   0.0507    10.28  0.00    0.0541       9.63        0.00
b_logpnetincome 0.432   0.0514    8.40   0.00    0.0536       8.06        0.00
b_work          0.0214  0.0360    0.59   0.55  * 0.0359       0.60        0.55       *
const           -6.61   0.616     -10.74 0.00    0.627        -10.54      0.00
eta_c           -0.0687 0.00887   -7.75  0.00    0.00901      -7.62       0.00
eta_t           0.0782  0.00884   8.85   0.00    0.00961      8.14        0.00
p_one           1.00    --fixed--
sigma           1.37    0.183     7.48   0.00    0.210        6.54        0.00

Homogeneity parameter (mu)
**************************
Value Std err t-test(0) p-val(0) t-test (1) p-val(1) Rob. std err Rob. t-test(0) Rob. p-val(0) Rob. t-
test(1) Rob. p-val(1)
----- ------- --------- -------- ---------- -------- ------------ -------------- ------------- ------------
-- -------------
2.44  0.0386  63.17     0.00     37.26      0.00     0.0497       49.01          0.00          28.90
0.00


Variance of normal random coefficients
**************************************
Name        Value Std err t-test
----        ----- ------- ------
const_sigma 1.88  0.503   3.74
```

Figure A.15: Results for Extended Base Model

```
                         Model:  Mixed Multinomial Logit for panel data
               Number of draws: 725
Number of estimated parameters: 22
        Number of observations: 24768
         Number of individuals: 3097
           Null log-likelihood: -17167.869
            Cte log-likelihood: -15611.938
           Init log-likelihood: -9610.358
          Final log-likelihood: -9589.803
         Likelihood ratio test: 15156.132
                    Rho-square: 0.441
           Adjusted rho-square: 0.440
           Final gradient norm: +6.486e-02
                    Diagnostic: Convergence reached...
                    Iterations: 28
                      Run time: 08h 48:48
           Variance-covariance: from finite difference hessian
                   Sample file: car_short_final_w.dat

Utility parameters
******************
Name            Value   Std err   t-test p-val   Rob. std err Rob. t-test Rob. p-val
----            -----   -------   ------ -----   ------------ ----------- ----------
B_FLEXIBLE      0.117   0.0370    3.16   0.00    0.0376       3.11        0.00
B_NOPAY         0.203   0.0639    3.18   0.00    0.0662       3.07        0.00
B_NOWALK        0.119   0.0378    3.15   0.00    0.0403       2.95        0.00
B_OSLO          0.122   0.0559    2.19   0.03    0.0557       2.20        0.03
SNP1            0.0679  0.0748    0.91   0.36  * 0.110        0.62        0.54       *
SNP2            -0.219  0.0615    -3.55  0.00    0.0944       -2.31       0.02
SNP3            -0.126  0.0553    -2.28  0.02    0.0682       -1.85       0.06       *
SNP4            0.159   0.0310    5.14   0.00    0.0419       3.81        0.00
b_age           0.00169 0.00888   0.19   0.85  * 0.00939      0.18        0.86       *
b_agesq         -0.0196 0.00936   -2.09  0.04    0.00991      -1.98       0.05
b_female        -0.0779 0.0371    -2.10  0.04    0.0378       -2.06       0.04
b_income_miss   5.06    0.655     7.72   0.00    0.686        7.38        0.00
b_logdT         0.0802  0.0245    3.28   0.00    0.0268       3.00        0.00
b_logdistance   -0.152  0.0554    -2.75  0.01    0.0595       -2.56       0.01
b_logjcost      0.488   0.0516    9.46   0.00    0.0565       8.64        0.00
b_logpnetincome 0.414   0.0518    7.99   0.00    0.0542       7.65        0.00
b_work          0.0169  0.0362    0.47   0.64  * 0.0378       0.45        0.65       *
const           -6.64   0.617     -10.77 0.00    0.636        -10.44      0.00
eta_c           -0.0685 0.00887   -7.72  0.00    0.00903      -7.58       0.00
eta_t           0.0782  0.00883   8.86   0.00    0.00960      8.15        0.00
p_one           1.00    --fixed--
sigma           1.28    0.148     8.61   0.00    0.205        6.23        0.00

Homogeneity parameter (mu)
**************************
Value Std err t-test(0) p-val(0) t-test (1) p-val(1) Rob. std err Rob. t-test(0) Rob. p-val(0) Rob. t-
test(1) Rob. p-val(1)
----- ------- --------- -------- ---------- -------- ------------ -------------- ------------- ------------
-- -------------
2.44  0.0386  63.17     0.00     37.24      0.00     0.0497       49.02          0.00          28.90
0.00


Variance of normal random coefficients
**************************************
Name        Value Std err t-test
----        ----- ------- ------
const_sigma 1.63  0.379   4.30
```

Figure A.16: Results for Extended Base Model (Missing incomes removed)

```
                         Model:  Mixed Multinomial Logit for panel data
               Number of draws: 725
Number of estimated parameters: 21
       Number of observations: 23520
        Number of individuals: 2941
          Null log-likelihood: -16302.822
           Cte log-likelihood: -14865.404
          Init log-likelihood: -9155.139
         Final log-likelihood: -9139.230
        Likelihood ratio test: 14327.184
                   Rho-square: 0.439
          Adjusted rho-square: 0.438
          Final gradient norm: +2.679e-02
                   Diagnostic: Convergence reached...
                   Iterations: 21
                     Run time: 03h 32:20
          Variance-covariance: from finite difference hessian
                  Sample file: car_short_final_w.dat

Utility parameters
******************
Name            Value    Std err   t-test p-val   Rob. std err Rob. t-test Rob. p-val
----            -----    -------   ------ -----   ------------ ----------- ----------
B_FLEXIBLE      0.103    0.0377    2.74   0.01    0.0380       2.72        0.01
B_NOPAY         0.171    0.0662    2.59   0.01    0.0688       2.49        0.01
B_NOWALK        0.112    0.0386    2.90   0.00    0.0403       2.78        0.01
B_OSLO          0.0918   0.0576    1.59   0.11  * 0.0574       1.60        0.11       *
SNP1            -0.102   0.0758    -1.34  0.18  * 0.0991       -1.03       0.31       *
SNP2            -0.230   0.0542    -4.24  0.00    0.0588       -3.91       0.00
SNP3            -0.00418 0.0560    -0.07  0.94  * 0.0733       -0.06       0.95       *
SNP4            0.153    0.0281    5.47   0.00    0.0307       5.00        0.00
b_age           0.00258  0.00945   0.27   0.78  * 0.0104       0.25        0.80       *
b_agesq         -0.0201  0.00992   -2.03  0.04    0.0110       -1.84       0.07       *
b_female        -0.0749  0.0383    -1.95  0.05  * 0.0391       -1.92       0.06       *
b_logdT         0.0651   0.0251    2.60   0.01    0.0274       2.37        0.02
b_logdistance   -0.147   0.0565    -2.60  0.01    0.0592       -2.48       0.01
b_logjcost      0.491    0.0528    9.30   0.00    0.0568       8.65        0.00
b_logpnetincome 0.423    0.0522    8.10   0.00    0.0551       7.67        0.00
b_work          0.0185   0.0366    0.51   0.61  * 0.0365       0.51        0.61       *
const           -6.47    0.621     -10.43 0.00    0.652        -9.92       0.00
eta_c           -0.0684  0.00910   -7.52  0.00    0.00925      -7.39       0.00
eta_t           0.0784   0.00907   8.65   0.00    0.00985      7.96        0.00
p_one           1.00     --fixed--
sigma           1.27     0.138     9.21   0.00    0.152        8.38        0.00

Homogeneity parameter (mu)
**************************
Value Std err t-test(0) p-val(0) t-test (1) p-val(1) Rob. std err Rob. t-test(0) Rob. p-val(0) Rob. t-
test(1) Rob. p-val(1)
----- ------- --------- -------- ---------- -------- ------------ -------------- ------------- ------------
-- -------------
2.43  0.0394  61.67     0.00     36.31      0.00     0.0510       47.69          0.00          28.08
0.00


Variance of normal random coefficients
**************************************
Name        Value Std err t-test
----        ----- ------- ------
const_sigma 1.61  0.350   4.60
```

Figure A.17: Results for Income Segmentation Model with 4 segments (Missing incomes removed)

```
                         Model:  Mixed Multinomial Logit for panel data
               Number of draws: 725
Number of estimated parameters: 24
        Number of observations: 23520
         Number of individuals: 2941
           Null log-likelihood: -16302.822
            Cte log-likelihood: -14865.404
           Init log-likelihood: -35858.851
          Final log-likelihood: -9134.595
         Likelihood ratio test: 14336.453
                    Rho-square: 0.440
           Adjusted rho-square: 0.438
           Final gradient norm: +2.049e-01
                    Diagnostic: Convergence reached...
                    Iterations: 43
                      Run time: 15h 30:57
           Variance-covariance: from finite difference hessian
                   Sample file: car_short_final_w.dat

Utility parameters
******************
Name          Value     Std err   t-test p-val   Rob. std err Rob. t-test Rob. p-val
----          -----     -------   ------ -----   ------------ ----------- ----------
B_FLEXIBLE    0.0945    0.0378    2.50   0.01    0.0381       2.48        0.01
B_INC1        -0.000388 0.269     -0.00  1.00  * 0.259        -0.00       1.00       *
B_INC2        0.465     0.140     3.32   0.00    0.144        3.24        0.00
B_INC3        0.384     0.181     2.12   0.03    0.183        2.09        0.04
B_INC4        1.24      0.385     3.21   0.00    0.412        3.01        0.00
B_NOPAY       0.146     0.0666    2.19   0.03    0.0695       2.10        0.04
B_NOWALK      0.115     0.0386    2.99   0.00    0.0404       2.86        0.00
B_OSLO        0.0896    0.0575    1.56   0.12  * 0.0573       1.56        0.12       *
SNP1          -0.0920   0.0733    -1.26  0.21  * 0.0933       -0.99       0.32       *
SNP2          -0.234    0.0539    -4.34  0.00    0.0593       -3.94       0.00
SNP3          -0.0119   0.0551    -0.22  0.83  * 0.0700       -0.17       0.87       *
SNP4          0.156     0.0280    5.59   0.00    0.0301       5.20        0.00
b_age         0.00577   0.00950   0.61   0.54  * 0.0105       0.55        0.58       *
b_agesq       -0.0230   0.00995   -2.31  0.02    0.0110       -2.09       0.04
b_female      -0.0701   0.0388    -1.81  0.07  * 0.0399       -1.76       0.08       *
b_logdT       0.0636    0.0251    2.54   0.01    0.0275       2.32        0.02
b_logdistance -0.141    0.0564    -2.51  0.01    0.0592       -2.39       0.02
b_logjcost    0.487     0.0528    9.21   0.00    0.0569       8.55        0.00
b_work        0.0216    0.0366    0.59   0.56  * 0.0365       0.59        0.55       *
const         -1.57     3.12      -0.50  0.61  * 2.97         -0.53       0.60       *
eta_c         -0.0684   0.00910   -7.52  0.00    0.00925      -7.39       0.00
eta_t         0.0784    0.00907   8.64   0.00    0.00985      7.96        0.00
p_one         1.00      --fixed--
sigma         1.28      0.140     9.10   0.00    0.156        8.16        0.00

Homogeneity parameter (mu)
*************************
Value Std err t-test(0) p-val(0) t-test (1) p-val(1) Rob. std err Rob. t-test(0) Rob. p-val(0) Rob. t-
test(1) Rob. p-val(1)
----- ------- --------- -------- ---------- -------- ------------ -------------- ------------- ------------
-- -------------
2.43  0.0394  61.67     0.00     36.31      0.00     0.0510       47.69          0.00          28.08
0.00


Variance of normal random coefficients
**************************************
Name        Value Std err t-test
----        ----- ------- ------
const_sigma 1.63  0.358   4.55
```

Figure A.18: Results for Extended Base Model with incomes above 150000 NOK (Missing incomes removed)

```
                         Model:  Mixed Multinomial Logit for panel data
               Number of draws: 725
Number of estimated parameters: 21
        Number of observations: 21617
         Number of individuals: 2703
           Null log-likelihood: -14983.763
            Cte log-likelihood: -13738.172
           Init log-likelihood: -8468.320
          Final log-likelihood: -8452.768
         Likelihood ratio test: 13061.990
                    Rho-square: 0.436
           Adjusted rho-square: 0.434
           Final gradient norm: +5.722e-02
                    Diagnostic: Convergence reached...
                    Iterations: 22
                      Run time: 04h 03:32
           Variance-covariance: from finite difference hessian
                   Sample file: car_short_final_w.dat

Utility parameters
******************
Name            Value   Std err   t-test p-val   Rob. std err Rob. t-test Rob. p-val
----            -----   -------   ------ -----   ------------ ----------- ----------
B_FLEXIBLE      0.105   0.0393    2.68   0.01    0.0396       2.65        0.01
B_NOPAY         0.124   0.0730    1.69   0.09  * 0.0757       1.63        0.10       *
B_NOWALK        0.111   0.0401    2.78   0.01    0.0431       2.58        0.01
B_OSLO          0.105   0.0596    1.75   0.08  * 0.0605       1.73        0.08       *
SNP1            -0.0483 0.0796    -0.61  0.54  * 0.114        -0.43       0.67       *
SNP2            -0.271  0.0587    -4.62  0.00    0.0692       -3.92       0.00
SNP3            -0.0376 0.0684    -0.55  0.58  * 0.0963       -0.39       0.70       *
SNP4            0.171   0.0350    4.88   0.00    0.0369       4.64        0.00
b_age           0.00151 0.0102    0.15   0.88  * 0.0113       0.13        0.89       *
b_agesq         -0.0181 0.0106    -1.71  0.09  * 0.0118       -1.54       0.12       *
b_female        -0.0405 0.0401    -1.01  0.31  * 0.0414       -0.98       0.33       *
b_logdT         0.0520  0.0260    2.00   0.05    0.0284       1.83        0.07       *
b_logdistance   -0.102  0.0590    -1.73  0.08  * 0.0640       -1.59       0.11       *
b_logjcost      0.458   0.0552    8.31   0.00    0.0608       7.53        0.00
b_logpnetincome 0.543   0.0733    7.41   0.00    0.0794       6.84        0.00
b_work          0.0116  0.0379    0.31   0.76  * 0.0383       0.30        0.76       *
const           -8.09   0.911     -8.89  0.00    0.987        -8.20       0.00
eta_c           -0.0658 0.00942   -6.98  0.00    0.00957      -6.87       0.00
eta_t           0.0774  0.00939   8.25   0.00    0.0102       7.59        0.00
p_one           1.00    --fixed--
sigma           1.37    0.171     8.01   0.00    0.201        6.82        0.00

Homogeneity parameter (mu)
**************************
Value Std err t-test(0) p-val(0) t-test (1) p-val(1) Rob. std err Rob. t-test(0) Rob. p-val(0) Rob. t-
test(1) Rob. p-val(1)
----- ------- --------- -------- ---------- -------- ------------ -------------- ------------- ------------
-- -------------
2.44  0.0411  59.39     0.00     35.05      0.00     0.0533       45.80          0.00          27.03
0.00


Variance of normal random coefficients
**************************************
Name        Value Std err t-test
----        ----- ------- ------
const_sigma 1.88  0.470   4.01
```

Figure A.19: Results for Income Segmentation Model with 3 segments with incomes above 150000 NOK (Missing incomes removed)

```
                         Model:  Mixed Multinomial Logit for panel data
               Number of draws: 725
Number of estimated parameters: 23
        Number of observations: 21617
         Number of individuals: 2703
           Null log-likelihood: -14983.763
            Cte log-likelihood: -13738.172
           Init log-likelihood: -33612.212
          Final log-likelihood: -8450.693
         Likelihood ratio test: 13066.139
                    Rho-square: 0.436
           Adjusted rho-square: 0.434
           Final gradient norm: +1.346e-01
                    Diagnostic: Convergence reached...
                    Iterations: 39
                      Run time: 16h 49:39
           Variance-covariance: from finite difference hessian
                   Sample file: car_short_final_w.dat

Utility parameters
******************
Name          Value   Std err   t-test p-val   Rob. std err Rob. t-test Rob. p-val
----          -----   -------   ------ -----   ------------ ----------- ----------
B_FLEXIBLE    0.102   0.0393    2.60   0.01    0.0397       2.58        0.01
B_INC2        0.448   0.175     2.56   0.01    0.180        2.50        0.01
B_INC3        0.422   0.185     2.28   0.02    0.187        2.26        0.02
B_INC4        1.25    0.388     3.23   0.00    0.417        3.01        0.00
B_NOPAY       0.124   0.0730    1.69   0.09  * 0.0755       1.64        0.10       *
B_NOWALK      0.110   0.0400    2.75   0.01    0.0430       2.56        0.01
B_OSLO        0.107   0.0596    1.79   0.07  * 0.0604       1.77        0.08       *
SNP1          -0.0567 0.0810    -0.70  0.48  * 0.118        -0.48       0.63       *
SNP2          -0.270  0.0572    -4.72  0.00    0.0650       -4.16       0.00
SNP3          -0.0334 0.0691    -0.48  0.63  * 0.0992       -0.34       0.74       *
SNP4          0.171   0.0346    4.92   0.00    0.0363       4.70        0.00
b_age         0.00269 0.0102    0.26   0.79  * 0.0113       0.24        0.81       *
b_agesq       -0.0194 0.0106    -1.84  0.07  * 0.0117       -1.66       0.10       *
b_female      -0.0472 0.0403    -1.17  0.24  * 0.0419       -1.13       0.26       *
b_logdT       0.0528  0.0260    2.03   0.04    0.0284       1.86        0.06       *
b_logdistance -0.101  0.0589    -1.72  0.09  * 0.0637       -1.59       0.11       *
b_logjcost    0.457   0.0552    8.29   0.00    0.0607       7.53        0.00
b_work        0.0145  0.0379    0.38   0.70  * 0.0382       0.38        0.70       *
const         -6.92   2.18      -3.18  0.00    2.25         -3.07       0.00
eta_c         -0.0658 0.00942   -6.98  0.00    0.00957      -6.87       0.00
eta_t         0.0774  0.00939   8.24   0.00    0.0102       7.58        0.00
p_one         1.00    --fixed--
sigma         1.37    0.166     8.22   0.00    0.189        7.23        0.00

Homogeneity parameter (mu)
*************************
Value Std err t-test(0) p-val(0) t-test (1) p-val(1) Rob. std err Rob. t-test(0) Rob. p-val(0) Rob. t-
test(1) Rob. p-val(1)
----- ------- --------- -------- ---------- -------- ------------ -------------- ------------- -----------
-- -------------
2.44  0.0411  59.39     0.00     35.05      0.00     0.0533       45.80          0.00          27.03
0.00


Variance of normal random coefficients
**************************************
Name        Value Std err t-test
----        ----- ------- ------
const_sigma 1.87  0.455   4.11
```

Figure A.20: Results for Extended Base Model for Men

```
                         Model:  Mixed Multinomial Logit for panel data
               Number of draws: 500
Number of estimated parameters: 21
        Number of observations: 13932
         Number of individuals: 1742
           Null log-likelihood: -9656.927
            Cte log-likelihood: -8955.959
           Init log-likelihood: -5485.836
          Final log-likelihood: -5463.650
         Likelihood ratio test: 8386.554
                    Rho-square: 0.434
           Adjusted rho-square: 0.432
           Final gradient norm: +2.642e-02
                    Diagnostic: Convergence reached...
                    Iterations: 22
                      Run time: 01h 53:24
           Variance-covariance: from finite difference hessian
                   Sample file: car_short_final_w.dat

Utility parameters
******************
Name            Value    Std err   t-test p-val   Rob. std err Rob. t-test Rob. p-val
----            -----    -------   ------ -----   ------------ ----------- ----------
B_FLEXIBLE      0.147    0.0484    3.05   0.00    0.0483       3.05        0.00
B_NOPAY         0.253    0.0833    3.04   0.00    0.0834       3.03        0.00
B_NOWALK        0.148    0.0493    3.00   0.00    0.0512       2.89        0.00
B_OSLO          0.114    0.0787    1.45   0.15  * 0.0787       1.45        0.15       *
SNP1            -0.0857  0.0663    -1.29  0.20  * 0.0680       -1.26       0.21       *
SNP2            -0.284   0.0600    -4.74  0.00    0.0584       -4.86       0.00
SNP3            0.00606  0.0599    0.10   0.92  * 0.0633       0.10        0.92       *
SNP4            0.172    0.0416    4.14   0.00    0.0401       4.30        0.00
b_age           -0.0245  0.0122    -2.01  0.04    0.0141       -1.74       0.08       *
b_agesq         0.00620  0.0126    0.49   0.62  * 0.0146       0.43        0.67       *
b_income_miss   6.20     0.935     6.63   0.00    0.989        6.27        0.00
b_logdT         0.0296   0.0330    0.90   0.37  * 0.0357       0.83        0.41       *
b_logdistance   -0.112   0.0700    -1.60  0.11  * 0.0730       -1.53       0.13       *
b_logjcost      0.478    0.0649    7.37   0.00    0.0691       6.91        0.00
b_logpnetincome 0.498    0.0733    6.80   0.00    0.0778       6.41        0.00
b_work          0.000296 0.0488    0.01   1.00  * 0.0485       0.01        1.00       *
const           -6.85    0.853     -8.03  0.00    0.871        -7.86       0.00
eta_c           -0.0673  0.0118    -5.68  0.00    0.0119       -5.68       0.00
eta_t           0.0785   0.0118    6.64   0.00    0.0131       6.01        0.00
p_one           1.00     --fixed--
sigma           1.45     0.180     8.05   0.00    0.178        8.17        0.00

Homogeneity parameter (mu)
**************************
Value Std err t-test(0) p-val(0) t-test (1) p-val(1) Rob. std err Rob. t-test(0) Rob. p-val(0) Rob. t-
test(1) Rob. p-val(1)
----- ------- --------- -------- ---------- -------- ------------ -------------- ------------- ------------
-- -------------
2.41  0.0506  47.72     0.00     27.95      0.00     0.0675       35.78          0.00          20.96
0.00


Variance of normal random coefficients
**************************************
Name        Value Std err t-test
----        ----- ------- ------
const_sigma 2.11  0.523   4.03
```

Figure A.21: Results for Extended Base Model for Women

```
                         Model:  Mixed Multinomial Logit for panel data
               Number of draws: 500
Number of estimated parameters: 21
        Number of observations: 10836
         Number of individuals: 1355
           Null log-likelihood: -7510.943
            Cte log-likelihood: -6632.154
           Init log-likelihood: -4123.852
          Final log-likelihood: -4113.413
         Likelihood ratio test: 6795.059
                    Rho-square: 0.452
           Adjusted rho-square: 0.450
           Final gradient norm: +1.020e-02
                    Diagnostic: Convergence reached...
                    Iterations: 28
                      Run time: 01h 52:23
           Variance-covariance: from finite difference hessian
                   Sample file: car_short_final_w.dat

Utility parameters
******************
Name            Value   Std err   t-test p-val   Rob. std err Rob. t-test Rob. p-val
----            -----   -------   ------ -----   ------------ ----------- ----------
B_FLEXIBLE      0.0600  0.0570    1.05   0.29  * 0.0588       1.02        0.31       *
B_NOPAY         0.0948  0.103     0.92   0.36  * 0.111        0.85        0.39       *
B_NOWALK        0.0660  0.0577    1.14   0.25  * 0.0619       1.07        0.29       *
B_OSLO          0.101   0.0816    1.24   0.21  * 0.0830       1.22        0.22       *
SNP1            0.0380  0.114     0.33   0.74  * 0.160        0.24        0.81       *
SNP2            -0.282  0.0626    -4.50  0.00    0.0671       -4.20       0.00
SNP3            -0.142  0.121     -1.17  0.24  * 0.164        -0.87       0.39       *
SNP4            0.201   0.0578    3.47   0.00    0.0619       3.24        0.00
b_age           0.0335  0.0155    2.17   0.03    0.0174       1.93        0.05       *
b_agesq         -0.0521 0.0173    -3.01  0.00    0.0197       -2.65       0.01
b_income_miss   4.00    0.916     4.36   0.00    0.969        4.13        0.00
b_logdT         0.150   0.0367    4.08   0.00    0.0403       3.71        0.00
b_logdistance   -0.244  0.0898    -2.71  0.01    0.0968       -2.52       0.01
b_logjcost      0.524   0.0830    6.31   0.00    0.0887       5.90        0.00
b_logpnetincome 0.330   0.0731    4.51   0.00    0.0775       4.25        0.00
b_work          0.0223  0.0534    0.42   0.68  * 0.0556       0.40        0.69       *
const           -6.28   0.856     -7.34  0.00    0.887        -7.09       0.00
eta_c           -0.0688 0.0134    -5.14  0.00    0.0138       -4.97       0.00
eta_t           0.0781  0.0133    5.87   0.00    0.0142       5.52        0.00
p_one           1.00    --fixed--
sigma           1.41    0.208     6.79   0.00    0.233        6.06        0.00

Homogeneity parameter (mu)
**************************
Value Std err t-test(0) p-val(0) t-test (1) p-val(1) Rob. std err Rob. t-test(0) Rob. p-val(0) Rob. t-
test(1) Rob. p-val(1)
----- ------- --------- -------- ---------- -------- ------------ -------------- ------------- ------------
-- -------------
2.47  0.0596  41.41     0.00     24.64      0.00     0.0726       34.00          0.00          20.23
0.00


Variance of normal random coefficients
**************************************
Name        Value Std err t-test
----        ----- ------- ------
const_sigma 1.98  0.585   3.39
```

Figure A.22: Results for Extended Base Model for Age segment 18-31

```
                         Model:  Mixed Multinomial Logit for panel data
               Number of draws: 500
Number of estimated parameters: 20
        Number of observations: 4129
         Number of individuals: 517
           Null log-likelihood: -2862.005
            Cte log-likelihood: -2687.769
           Init log-likelihood: -1591.892
          Final log-likelihood: -1567.346
         Likelihood ratio test: 2589.317
                    Rho-square: 0.452
           Adjusted rho-square: 0.445
           Final gradient norm: +1.459e-02
                    Diagnostic: Convergence reached...
                    Iterations: 525
                      Run time: 12h 49:51
           Variance-covariance: from finite difference hessian
                   Sample file: car_short_final_w.dat

Utility parameters
******************
Name            Value   Std err   t-test p-val   Rob. std err Rob. t-test Rob. p-val
----            -----   -------   ------ -----   ------------ ----------- ----------
B_FLEXIBLE      0.108   0.0830    1.30   0.19  * 0.0988       1.09        0.27       *
B_NOPAY         0.339   0.114     2.97   0.00    0.126        2.69        0.01
B_NOWALK        0.0179  0.0889    0.20   0.84  * 0.0958       0.19        0.85       *
B_OSLO          0.0984  0.114     0.86   0.39  * 0.109        0.90        0.37       *
SNP1            0.389   0.467     0.83   0.41  * 0.589        0.66        0.51       *
SNP2            -0.0766 0.0844    -0.91  0.36  * 0.0982       -0.78       0.44       *
SNP3            -0.362  0.365     -0.99  0.32  * 0.454        -0.80       0.43       *
SNP4            0.355   0.300     1.18   0.24  * 0.394        0.90        0.37       *
b_female        -0.311  0.0727    -4.29  0.00    0.0737       -4.23       0.00
b_income_miss   3.73    1.07      3.49   0.00    1.24         3.00        0.00
b_logdT         0.182   0.0535    3.41   0.00    0.0593       3.08        0.00
b_logdistance   -0.151  0.112     -1.35  0.18  * 0.116        -1.30       0.19       *
b_logjcost      0.388   0.0991    3.91   0.00    0.104        3.72        0.00
b_logpnetincome 0.301   0.0862    3.49   0.00    0.0998       3.01        0.00
b_work          0.0484  0.0761    0.64   0.52  * 0.0822       0.59        0.56       *
const           -5.23   1.10      -4.75  0.00    1.26         -4.14       0.00
eta_c           -0.0512 0.0198    -2.58  0.01    0.0200       -2.56       0.01
eta_t           0.0644  0.0197    3.26   0.00    0.0210       3.06        0.00
p_one           1.00    --fixed--
sigma           0.984   0.140     7.05   0.00    0.171        5.76        0.00

Homogeneity parameter (mu)
**************************
Value Std err t-test(0) p-val(0) t-test (1) p-val(1) Rob. std err Rob. t-test(0) Rob. p-val(0) Rob. t-
test(1) Rob. p-val(1)
----- ------- --------- -------- ---------- -------- ------------ -------------- ------------- ------------
-- -------------
2.72  0.104   26.04     0.00     16.46      0.00     0.132        20.55          0.00          12.99
0.00


Variance of normal random coefficients
**************************************
Name        Value Std err t-test
----        ----- ------- ------
const_sigma 0.969 0.275   3.52
```

Figure A.23: Results for Extended Base Model for Age segment 32-38

```
                        Model:  Mixed Multinomial Logit for panel data
              Number of draws: 500
Number of estimated parameters: 20
        Number of observations: 3088
         Number of individuals: 386
           Null log-likelihood: -2140.438
            Cte log-likelihood: -2040.853
           Init log-likelihood: -1252.312
          Final log-likelihood: -1235.620
         Likelihood ratio test: 1809.636
                    Rho-square: 0.423
           Adjusted rho-square: 0.413
           Final gradient norm: +1.137e-02
                    Diagnostic: Convergence reached...
                    Iterations: 214
                      Run time: 03h 54:09
           Variance-covariance: from finite difference hessian
                   Sample file: car_short_final_w.dat

Utility parameters
******************
Name            Value   Std err   t-test p-val   Rob. std err Rob. t-test Rob. p-val
----            -----   -------   ------ -----   ------------ ----------- ----------
B_FLEXIBLE      0.152   0.0849    1.79   0.07  * 0.0916       1.66        0.10       *
B_NOPAY         -0.107  0.137     -0.78  0.43  * 0.152        -0.71       0.48       *
B_NOWALK        0.163   0.0909    1.79   0.07  * 0.0980       1.66        0.10       *
B_OSLO          0.0467  0.101     0.46   0.64  * 0.0967       0.48        0.63       *
SNP1            0.117   0.141     0.83   0.41  * 0.178        0.66        0.51       *
SNP2            -0.163  0.0537    -3.03  0.00    0.0599       -2.72       0.01
SNP3            -0.181  0.125     -1.45  0.15  * 0.152        -1.19       0.23       *
SNP4            0.376   0.148     2.55   0.01    0.201        1.87        0.06       *
b_female        -0.166  0.0813    -2.04  0.04    0.0865       -1.92       0.05       *
b_income_miss   4.07    1.62      2.51   0.01    1.90         2.14        0.03
b_logdT         -0.0422 0.0596    -0.71  0.48  * 0.0609       -0.69       0.49       *
b_logdistance   -0.183  0.118     -1.55  0.12  * 0.125        -1.47       0.14       *
b_logjcost      0.532   0.104     5.11   0.00    0.106        5.00        0.00
b_logpnetincome 0.386   0.127     3.05   0.00    0.151        2.56        0.01
b_work          -0.0583 0.0777    -0.75  0.45  * 0.0825       -0.71       0.48       *
const           -6.16   1.62      -3.80  0.00    1.91         -3.22       0.00
eta_c           -0.0363 0.0233    -1.56  0.12  * 0.0248       -1.46       0.14       *
eta_t           0.0336  0.0230    1.46   0.14  * 0.0238       1.41        0.16       *
p_one           1.00    --fixed--
sigma           0.915   0.125     7.29   0.00    0.168        5.46        0.00

Homogeneity parameter (mu)
**************************
Value Std err t-test(0) p-val(0) t-test (1) p-val(1) Rob. std err Rob. t-test(0) Rob. p-val(0) Rob. t-
test(1) Rob. p-val(1)
----- ------- --------- -------- ---------- -------- ------------ -------------- ------------- ------------
-- -------------
2.56  0.110   23.40     0.00     14.27      0.00     0.136        18.89          0.00          11.52
0.00


Variance of normal random coefficients
**************************************
Name        Value Std err t-test
----        ----- ------- ------
const_sigma 0.837 0.229   3.65
```

Figure A.24: Results for Extended Base Model for Age segment 39-45

```
                         Model:  Mixed Multinomial Logit for panel data
               Number of draws: 500
Number of estimated parameters: 20
        Number of observations: 4856
         Number of individuals: 607
           Null log-likelihood: -3365.923
            Cte log-likelihood: -3168.856
           Init log-likelihood: -1923.579
          Final log-likelihood: -1891.357
         Likelihood ratio test: 2949.131
                    Rho-square: 0.438
           Adjusted rho-square: 0.432
           Final gradient norm: +1.370e-02
                    Diagnostic: Convergence reached...
                    Iterations: 20
                      Run time: 36:03
           Variance-covariance: from finite difference hessian
                   Sample file: car_short_final_w.dat

Utility parameters
******************
Name            Value   Std err   t-test p-val   Rob. std err Rob. t-test Rob. p-val
----            -----   -------   ------ -----   ------------ ----------- ----------
B_FLEXIBLE      0.269   0.0739    3.65   0.00    0.0752       3.58        0.00
B_NOPAY         0.0524  0.139     0.38   0.71  * 0.155        0.34        0.74       *
B_NOWALK        0.234   0.0783    2.99   0.00    0.0781       2.99        0.00
B_OSLO          0.242   0.122     1.99   0.05    0.118        2.06        0.04
SNP1            -0.152  0.118     -1.29  0.20  * 0.132        -1.15       0.25       *
SNP2            -0.358  0.108     -3.31  0.00    0.133        -2.70       0.01
SNP3            0.0581  0.121     0.48   0.63  * 0.132        0.44        0.66       *
SNP4            0.252   0.110     2.28   0.02    0.125        2.01        0.04
b_female        0.157   0.0800    1.96   0.05    0.0861       1.82        0.07       *
b_income_miss   3.33    1.55      2.15   0.03    1.69         1.96        0.05
b_logdT         0.0238  0.0531    0.45   0.65  * 0.0598       0.40        0.69       *
b_logdistance   -0.0231 0.118     -0.19  0.85  * 0.122        -0.19       0.85       *
b_logjcost      0.456   0.115     3.98   0.00    0.124        3.67        0.00
b_logpnetincome 0.271   0.122     2.22   0.03    0.134        2.02        0.04
b_work          -0.0761 0.0739    -1.03  0.30  * 0.0760       -1.00       0.32       *
const           -5.07   1.59      -3.19  0.00    1.78         -2.85       0.00
eta_c           -0.0757 0.0189    -4.01  0.00    0.0194       -3.89       0.00
eta_t           0.0473  0.0189    2.50   0.01    0.0199       2.38        0.02
p_one           1.00    --fixed--
sigma           1.57    0.346     4.53   0.00    0.429        3.65        0.00

Homogeneity parameter (mu)
**************************
Value Std err t-test(0) p-val(0) t-test (1) p-val(1) Rob. std err Rob. t-test(0) Rob. p-val(0) Rob. t-
test(1) Rob. p-val(1)
----- ------- --------- -------- ---------- -------- ------------ -------------- ------------- ------------
-- -------------
2.57  0.0891  28.91     0.00     17.68      0.00     0.111        23.12          0.00          14.14
0.00


Variance of normal random coefficients
**************************************
Name        Value Std err t-test
----        ----- ------- ------
const_sigma 2.46  1.09    2.26
```

Figure A.25: Results for Extended Base Model for Age segment 46-52

```
                    Model:  Mixed Multinomial Logit for panel data
          Number of draws: 500
Number of estimated parameters: 20
       Number of observations: 4160
        Number of individuals: 520
          Null log-likelihood: -2883.492
           Cte log-likelihood: -2641.148
          Init log-likelihood: -1640.956
         Final log-likelihood: -1600.693
        Likelihood ratio test: 2565.598
                   Rho-square: 0.445
          Adjusted rho-square: 0.438
          Final gradient norm: +1.085e-02
                   Diagnostic: Convergence reached...
                   Iterations: 32
                     Run time: 47:18
          Variance-covariance: from finite difference hessian
                  Sample file: car_short_final_w.dat

Utility parameters
******************
Name            Value   Std err   t-test p-val   Rob. std err Rob. t-test Rob. p-val
----            -----   -------   ------ -----   ------------ ----------- ----------
B_FLEXIBLE      -0.0572 0.0889    -0.64  0.52  * 0.0982       -0.58       0.56       *
B_NOPAY         0.402   0.168     2.40   0.02    0.191        2.10        0.04
B_NOWALK        0.0942  0.0863    1.09   0.27  * 0.0887       1.06        0.29       *
B_OSLO          0.0645  0.147     0.44   0.66  * 0.166        0.39        0.70       *
SNP1            0.0496  0.160     0.31   0.76  * 0.203        0.24        0.81       *
SNP2            -0.444  0.121     -3.68  0.00    0.156        -2.85       0.00
SNP3            -0.0395 0.197     -0.20  0.84  * 0.207        -0.19       0.85       *
SNP4            0.268   0.145     1.85   0.06  * 0.132        2.03        0.04
b_female        -0.0365 0.0857    -0.43  0.67  * 0.0874       -0.42       0.68       *
b_income_miss   8.30    1.76      4.73   0.00    1.93         4.30        0.00
b_logdT         0.214   0.0581    3.68   0.00    0.0676       3.16        0.00
b_logdistance   -0.446  0.141     -3.16  0.00    0.177        -2.52       0.01
b_logjcost      0.683   0.135     5.06   0.00    0.179        3.82        0.00
b_logpnetincome 0.647   0.138     4.71   0.00    0.149        4.34        0.00
b_work          0.146   0.0833    1.75   0.08  * 0.0872       1.67        0.09       *
const           -10.0   1.80      -5.58  0.00    1.99         -5.04       0.00
eta_c           -0.0439 0.0212    -2.07  0.04    0.0215       -2.04       0.04
eta_t           0.0824  0.0212    3.89   0.00    0.0234       3.53        0.00
p_one           1.00    --fixed--
sigma           1.78    0.373     4.77   0.00    0.441        4.04        0.00

Homogeneity parameter (mu)
**************************
Value Std err t-test(0) p-val(0) t-test (1) p-val(1) Rob. std err Rob. t-test(0) Rob. p-val(0) Rob. t-
test(1) Rob. p-val(1)
----- ------- --------- -------- ---------- -------- ------------ -------------- ------------- ------------
-- -------------
2.48  0.0959  25.83     0.00     15.40      0.00     0.115        21.54          0.00          12.84
0.00


Variance of normal random coefficients
**************************************
Name        Value Std err t-test
----        ----- ------- ------
const_sigma 3.17  1.33    2.38
```

Figure A.26: Results for Extended Base Model for Age segment 53-59

```
                         Model:  Mixed Multinomial Logit for panel data
               Number of draws: 500
Number of estimated parameters: 20
        Number of observations: 3703
         Number of individuals: 463
           Null log-likelihood: -2566.724
            Cte log-likelihood: -2257.863
           Init log-likelihood: -1508.517
          Final log-likelihood: -1457.694
         Likelihood ratio test: 2218.060
                    Rho-square: 0.432
           Adjusted rho-square: 0.424
           Final gradient norm: +1.262e-02
                    Diagnostic: Convergence reached...
                    Iterations: 231
                      Run time: 04h 56:51
           Variance-covariance: from finite difference hessian
                   Sample file: car_short_final_w.dat

Utility parameters
******************
Name            Value    Std err   t-test p-val   Rob. std err Rob. t-test Rob. p-val
----            -----    -------   ------ -----   ------------ ----------- ----------
B_FLEXIBLE      0.00906  0.109     0.08   0.93  * 0.111        0.08        0.94       *
B_NOPAY         -0.00473 0.177     -0.03  0.98  * 0.171        -0.03       0.98       *
B_NOWALK        -0.0300  0.106     -0.28  0.78  * 0.112        -0.27       0.79       *
B_OSLO          0.377    0.193     1.95   0.05  * 0.191        1.97        0.05
SNP1            0.494    0.229     2.16   0.03    0.173        2.86        0.00
SNP2            -0.590   0.181     -3.26  0.00    0.119        -4.97       0.00
SNP3            -0.548   0.127     -4.31  0.00    0.120        -4.57       0.00
SNP4            0.660    0.132     5.00   0.00    0.117        5.62        0.00
b_female        -0.159   0.110     -1.44  0.15  * 0.110        -1.45       0.15       *
b_income_miss   4.84     1.98      2.44   0.01    1.99         2.43        0.02
b_logdT         0.0147   0.0707    0.21   0.84  * 0.0725       0.20        0.84       *
b_logdistance   0.101    0.177     0.57   0.57  * 0.215        0.47        0.64       *
b_logjcost      0.366    0.150     2.43   0.01    0.177        2.06        0.04
b_logpnetincome 0.434    0.156     2.78   0.01    0.157        2.77        0.01
b_work          0.0218   0.101     0.22   0.83  * 0.103        0.21        0.83       *
const           -7.77    1.97      -3.95  0.00    1.98         -3.93       0.00
eta_c           -0.101   0.0256    -3.94  0.00    0.0262       -3.84       0.00
eta_t           0.119    0.0255    4.65   0.00    0.0290       4.10        0.00
p_one           1.00     --fixed--
sigma           2.41     0.253     9.56   0.00    0.206        11.73       0.00

Homogeneity parameter (mu)
**************************
Value Std err t-test(0) p-val(0) t-test (1) p-val(1) Rob. std err Rob. t-test(0) Rob. p-val(0) Rob. t-
test(1) Rob. p-val(1)
----- ------- --------- -------- ---------- -------- ------------ -------------- ------------- ------------
-- -------------
2.17  0.0919  23.63     0.00     12.74      0.00     0.121        17.99          0.00          9.70
0.00


Variance of normal random coefficients
**************************************
Name        Value Std err t-test
----        ----- ------- ------
const_sigma 5.83  1.22    4.78
```

Figure A.27: Results for Extended Base Model for Age segment 60+

```
                         Model:  Mixed Multinomial Logit for panel data
               Number of draws: 500
Number of estimated parameters: 20
        Number of observations: 4832
         Number of individuals: 604
           Null log-likelihood: -3349.287
            Cte log-likelihood: -2701.714
           Init log-likelihood: -1878.447
          Final log-likelihood: -1736.100
         Likelihood ratio test: 3226.375
                    Rho-square: 0.482
           Adjusted rho-square: 0.476
           Final gradient norm: +1.214e-02
                    Diagnostic: Convergence reached...
                    Iterations: 385
                      Run time: 10h 49:28
           Variance-covariance: from finite difference hessian
                   Sample file: car_short_final_w.dat

Utility parameters
******************
Name            Value   Std err   t-test p-val   Rob. std err Rob. t-test Rob. p-val
----            -----   -------   ------ -----   ------------ ----------- ----------
B_FLEXIBLE      0.152   0.0989    1.54   0.12  * 0.0970       1.57        0.12       *
B_NOPAY         0.495   0.224     2.21   0.03    0.220        2.25        0.02
B_NOWALK        0.170   0.0890    1.91   0.06  * 0.0927       1.83        0.07       *
B_OSLO          -0.0497 0.149     -0.33  0.74  * 0.161        -0.31       0.76       *
SNP1            -0.275  0.129     -2.12  0.03    0.132        -2.07       0.04
SNP2            -0.355  0.124     -2.86  0.00    0.109        -3.25       0.00
SNP3            0.135   0.159     0.85   0.39  * 0.189        0.71        0.48       *
SNP4            0.0887  0.0825    1.08   0.28  * 0.0810       1.09        0.27       *
b_female        -0.0291 0.107     -0.27  0.79  * 0.109        -0.27       0.79       *
b_income_miss   8.09    1.79      4.51   0.00    1.92         4.22        0.00
b_logdT         0.0640  0.0648    0.99   0.32  * 0.0721       0.89        0.37       *
b_logdistance   0.00239 0.137     0.02   0.99  * 0.143        0.02        0.99       *
b_logjcost      0.372   0.126     2.94   0.00    0.129        2.88        0.00
b_logpnetincome 0.629   0.142     4.45   0.00    0.152        4.14        0.00
b_work          0.0896  0.109     0.83   0.41  * 0.105        0.85        0.39       *
const           -9.58   1.78      -5.38  0.00    1.86         -5.14       0.00
eta_c           -0.103  0.0230    -4.47  0.00    0.0225       -4.58       0.00
eta_t           0.134   0.0229    5.84   0.00    0.0259       5.16        0.00
p_one           1.00    --fixed--
sigma           1.73    0.376     4.61   0.00    0.398        4.36        0.00

Homogeneity parameter (mu)
**************************
Value Std err t-test(0) p-val(0) t-test (1) p-val(1) Rob. std err Rob. t-test(0) Rob. p-val(0) Rob. t-
test(1) Rob. p-val(1)
----- ------- --------- -------- ---------- -------- ------------ -------------- ------------- ------------
-- -------------
2.20  0.0840  26.19     0.00     14.28      0.00     0.115        19.12          0.00          10.42
0.00


Variance of normal random coefficients
**************************************
Name        Value Std err t-test
----        ----- ------- ------
const_sigma 3.01  1.31    2.31
```

Figure A.28: Results for Base Model used in the Norwegian Value of Time Study (Ramjerdi, 2010) for public transport short distance travel segment

```
                         Model:  Mixed Multinomial Logit for panel data
        Number of Halton draws: 1000
Number of estimated parameters: 18
        Number of observations: 4568
         Number of individuals: 571
           Null log-likelihood: -3166.296
            Cte log-likelihood: -2714.220
           Init log-likelihood: -1666.009
          Final log-likelihood: -1664.847
         Likelihood ratio test: 3002.898
                    Rho-square: 0.474
           Adjusted rho-square: 0.469
           Final gradient norm: +1.845e-02
                    Diagnostic: Convergence reached...
                    Iterations: 75
                      Run time: 01h 21:54
           Variance-covariance: from finite difference hessian
                   Sample file: PT_short_final_w.dat

Utility parameters
******************
Name            Value   Std err   t-test p-val   Rob. std err Rob. t-test Rob. p-val
----            -----   -------   ------ -----   ------------ ----------- ----------
SNP1            0.709   0.502     1.41   0.16  * 0.207        3.43        0.00
SNP2            0.468   0.589     0.79   0.43  * 0.206        2.27        0.02
SNP3            -0.209  0.951     -0.22  0.83  * 0.335        -0.62       0.53       *
SNP4            -0.495  0.859     -0.58  0.56  * 0.264        -1.87       0.06       *
b_age           0.0130  0.0190    0.69   0.49  * 0.0210       0.62        0.53       *
b_agesq         -0.0268 0.0209    -1.29  0.20  * 0.0232       -1.15       0.25       *
b_female        0.00551 0.0783    0.07   0.94  * 0.0834       0.07        0.95       *
b_income_miss   7.59    1.28      5.95   0.00    1.39         5.45        0.00
b_logdT         0.0566  0.0485    1.17   0.24  * 0.0535       1.06        0.29       *
b_logdistance   0.0421  0.0489    0.86   0.39  * 0.0476       0.88        0.38       *
b_logjcost      0.284   0.0876    3.24   0.00    0.0938       3.03        0.00
b_logpnetincome 0.617   0.102     6.03   0.00    0.113        5.47        0.00
b_work          -0.0273 0.0843    -0.32  0.75  * 0.0895       -0.30       0.76       *
const           -10.7   1.28      -8.33  0.00    1.31         -8.17       0.00
eta_c           -0.145  0.0195    -7.44  0.00    0.0220       -6.61       0.00
eta_t           0.0429  0.0192    2.23   0.03    0.0212       2.02        0.04
p_one           1.00    --fixed--
sigma           1.46    0.323     4.51   0.00    0.163        8.93        0.00

Homogeneity parameter (mu)
*************************
Value Std err t-test(0) p-val(0) t-test (1) p-val(1) Rob. std err Rob. t-test(0) Rob. p-val(0) Rob. t-
test(1) Rob. p-val(1)
----- ------- --------- -------- ---------- -------- ------------ -------------- ------------- ------------
-- -------------
2.68  0.103   26.12     0.00     16.37      0.00     0.116        23.00          0.00          14.41
0.00


Variance of normal random coefficients
**************************************
Name        Value Std err t-test
----        ----- ------- ------
const_sigma 2.13  0.943   2.26
```

Figure A.29: Results for Extended Base Model for public transport short distance travel segment

```
                         Model:  Mixed Multinomial Logit for panel data
        Number of Halton draws: 1000
Number of estimated parameters: 19
        Number of observations: 4568
         Number of individuals: 571
           Null log-likelihood: -3166.296
            Cte log-likelihood: -2714.220
           Init log-likelihood: -1666.009
          Final log-likelihood: -1660.837
         Likelihood ratio test: 3010.919
                    Rho-square: 0.475
           Adjusted rho-square: 0.469
           Final gradient norm: +5.882e-03
                    Diagnostic: Convergence reached...
                    Iterations: 78
                      Run time: 02h 38:17
           Variance-covariance: from finite difference hessian
                   Sample file: pt_short_final_w.dat

Utility parameters
******************
Name            Value    Std err   t-test p-val   Rob. std err Rob. t-test Rob. p-val
----            -----    -------   ------ -----   ------------ ----------- ----------
B_OSLO          -0.223   0.0777    -2.87  0.00    0.0776       -2.87       0.00
SNP1            0.679    0.257     2.64   0.01    0.108        6.26        0.00
SNP2            0.543    0.435     1.25   0.21  * 0.183        2.96        0.00
SNP3            -0.241   0.815     -0.30  0.77  * 0.332        -0.72       0.47       *
SNP4            -0.430   0.709     -0.61  0.54  * 0.240        -1.79       0.07       *
b_age           0.0142   0.0188    0.75   0.45  * 0.0206       0.69        0.49       *
b_agesq         -0.0293  0.0206    -1.42  0.16  * 0.0228       -1.28       0.20       *
b_female        -0.00134 0.0761    -0.02  0.99  * 0.0791       -0.02       0.99       *
b_income_miss   7.70     1.25      6.17   0.00    1.35         5.70        0.00
b_logdT         0.0501   0.0482    1.04   0.30  * 0.0533       0.94        0.35       *
b_logdistance   0.00915  0.0492    0.19   0.85  * 0.0480       0.19        0.85       *
b_logjcost      0.255    0.0866    2.94   0.00    0.0913       2.79        0.01
b_logpnetincome 0.624    0.100     6.23   0.00    0.109        5.70        0.00
b_work          -0.0442  0.0822    -0.54  0.59  * 0.0858       -0.51       0.61       *
const           -10.4    1.24      -8.34  0.00    1.29         -8.01       0.00
eta_c           -0.146   0.0195    -7.46  0.00    0.0220       -6.62       0.00
eta_t           0.0431   0.0192    2.24   0.02    0.0212       2.03        0.04
p_one           1.00     --fixed--
sigma           1.34     0.348     3.84   0.00    0.189        7.10        0.00

Homogeneity parameter (mu)
*************************
Value Std err t-test(0) p-val(0) t-test (1) p-val(1) Rob. std err Rob. t-test(0) Rob. p-val(0) Rob. t-
test(1) Rob. p-val(1)
----- ------- --------- -------- ---------- -------- ------------ -------------- ------------- ------------
-- -------------
2.68  0.103   26.14     0.00     16.38      0.00     0.116        23.04          0.00          14.44
0.00


Variance of normal random coefficients
**************************************
Name        Value Std err t-test
----        ----- ------- ------
const_sigma 1.79  0.933   1.92
```