Values of travel time in the AKTA project

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1. INTRODUCTION

AKTA (http://www.akta-kbh.dk) is a research study under the EU-project PROGRESS (www.progress-project.org), which is part of the EU's 5th framework programme named 'The Growth Programme on Sustainable Mobility and Intermodality'. The programme supports several studies related to road pricing and similar subjects in traffic planning. PROGRESS includes eight European cities that research in different types of tolls. These cities are Bristol and Edinburgh (UK), Genoa and Rom (Italy), Helsinki (Finland), Trondheim (Norway), Gothenburg (Sweden) and Copenhagen. AKTA's deadline is in autumn 2003, after a 3½ year long project period. The budget in the study is about DKK 13.5 million. More about the project itself can be found in Nielsen & Herslund, 2002 and Nielsen & Jovicic, 2003.

The aim of the paper is to present the obtained values of travel time (VOT) in the AKTA SP project. Basis for the VOT is Stated Preference (SP) data, which has been collected specifically for the purposes of the project. Three main effects are described in the paper:

1. *methodological effect;* respondents' perception of VOT based on presented travel costs versus travel distances in the SP experiments,
2. *theoretical effect;* differences in the obtained VOT based on ordinary MNL models and Error Component (EC) models, and
3. *income effect;* differences in the obtained VOT with and without the income effect.

Section two describes AKTA's SP survey. The following section depicts some important theoretical aspects of the VOT in logit models. Section four is the main part of the paper where the modelling work is presented. Concluding discussion and remarks are given in the last section.

2. SP SURVEY

A SP survey has been completed in the study. A group of 300 car drivers were sampled for a computer based interview that took place while the respondents waited for a GPS-unit to be installed in the car. All respondents owned only one car in the family and they were all employed.

279 interviews were successfully completed. If the respondent usually travelled to work by car the most recent car-commuting trip was described in the first part of the interview. If not a commuting trip then the respondent was asked to describe a trip for another

travel purpose. Questions regarding the chosen trip included origin and destination addresses, departure and arrival times, and travel purpose. If the respondent completed an extra activity on the way (e.g. shopping, visiting bank) these activities were notified. It was the departure time that decided if the trip should be understood as a ‘peak’ or an ‘out-of-peak’ trip. The peak periods were defined between 7a.m. and 9.30a.m. (morning peak), and between 3p.m. and 5.30p.m. (afternoon peak).

Five SP experiments were defined in the questionnaire: SP1 and SP2 were VOT experiments, SP3 and SP4 were choice of time-of-day (TOD) experiments, and SP5 was a road pricing experiment. In all five experiments two travel time components were presented, i.e. free flow travel time and congested travel time. Free flow travel time was defined as travel time where the travel speed was not influenced by the presence of other cars on the road. Congested travel time is, on the other hand, influenced by the presence of other cars. As in prior Danish models (Nielsen et.al, 2002), it was defined as the time of the trip minus the time the trip would have taken if there were no congestion. Congested travel time is *not* necessarily the same as queuing time; Queuing time does not include all delays (e.g. slower speed before full queuing occur), but does also include some of the time the trip would have taken without queues. Queuing time is difficult to define in a SP-experiment, since different respondents have different thresholds for when they feel congestion reaches queuing. Some car users also tend to overestimate the time spent in queues.

Within the VOT and TOD experiments some respondents were presented with driving costs (in DKK) while others with driving distance (in meters). This approach was chosen because it was expected that travellers could relate themselves better to distances than to driving costs. If that proved to be correct, different VOT will be calculated for the two approaches. Not all the respondents were involved in the TOD experiments; the experiment was only carried out if they agreed that the opposite travel time (e.g. peak vs. off–peak) could be applied for the described trip. SP5 experiment included road pricing. An alternative route for the same origin-destination pair as in the original trip was found in cooperation between the respondent and the interviewer. Typically, the alternative route was longer (i.e., longer travel time) but it avoided those zones with high road pricing (typically the city centre). Table 1 lists the chosen variables in the SP experiments.

We ended up with 3,976 SP observations in the data, split in the following way:

- 1,671 observations in the VOT experiments (881 observation in the SP1 and 790 observations in the SP2),
- 636 observations in the TOD experiments (342 observation in the SP3 and 294 observations in the SP4), and
- 1,669 observations in the road pricing experiment (the SP5 experiment).

Those respondents who were presented with travel costs gave 14 SP responses in average, while those respondents presented with travel distances gave 14.5 SP responses in average. Maximum of 6 responses were defined in the SP experiments.

Table 1 – Variables in the SP experiments

	SP1 - VOT	SP2 - VOT	SP3 – TOD	SP4 – TOD	SP5 – Road Pricing
driving cost	√		√		√
driving distance		√		√	
road pricing					√
free flow travel time	√	√	√	√	√
congested travel time	√	√	√	√	√

3. THEORETICAL BACKGROUND

It is well known that time is costly. On the other hand, it is necessary for us to travel in order to execute activities at certain places and at certain times (an exception to that is travel for itself as for instance a bicycle tour in a weekend day). Travelling consumes therefore our time and we are willing to offer money in order to save it. Value of travel time (VOT) differs between men and women, young and older, employed and unemployed, and high and low income groups. VOT differs also within an individual in respect to travel mode, travel purpose, time of day travel (peak vs. out of peak). Finally, VOT is different for different travel time components, e.g. in vehicle travel time, access/egress, waiting time, interchanging time, delay time. This is because the possibilities of doing something useful (say, reading a book) while travelling are different for different travel time components and because of the comfort issue in general.

For a number of years discrete choice models have served for the purpose of calculating VOT. Most west European countries have developed studies with the only purpose of calculating VOT, which serve as input for different feasibility studies, i.e. CBA. Denmark has been exception to that until now. In other cases VOT are calculated in case specific projects. For instance, in the Ørestad Traffic Model (OTM) some 50 different VOT were calculated (Jovicic and Hansen, 2003).

In discrete choice models, which adopt the random utility paradigm, travel demand is defined via a utility function, which in a general formulation can take the following form:

$$U = tT + cC + sS + \varepsilon \qquad (1)$$

where, T stands for travel time, C for travel costs and S for socio-economic characteristics of the respondent. t, c and s are coefficients to be estimated, while ε is a random term. The coefficients in (1) are usually estimated by applying multinomial logit (MNL) models.

In the economic terminology, t is marginal utility of time and c marginal utility of cost. Therefore, VOT equals t/c and it has a unit in DKK per minute. Such VOT can be named as fixed VOT because both t and c have only one value in equation (1).

If we want to capture taste variation between the respondents, meaning that there is a variation around the mean value of the calculated VOT within the sample then we need to extend equation (1) by calculating standard deviations around say t coefficient. Taste variation across the sample is based on notion that socio-economic characteristics of respondents influence their VOT. In this case a new utility function can take the following form:

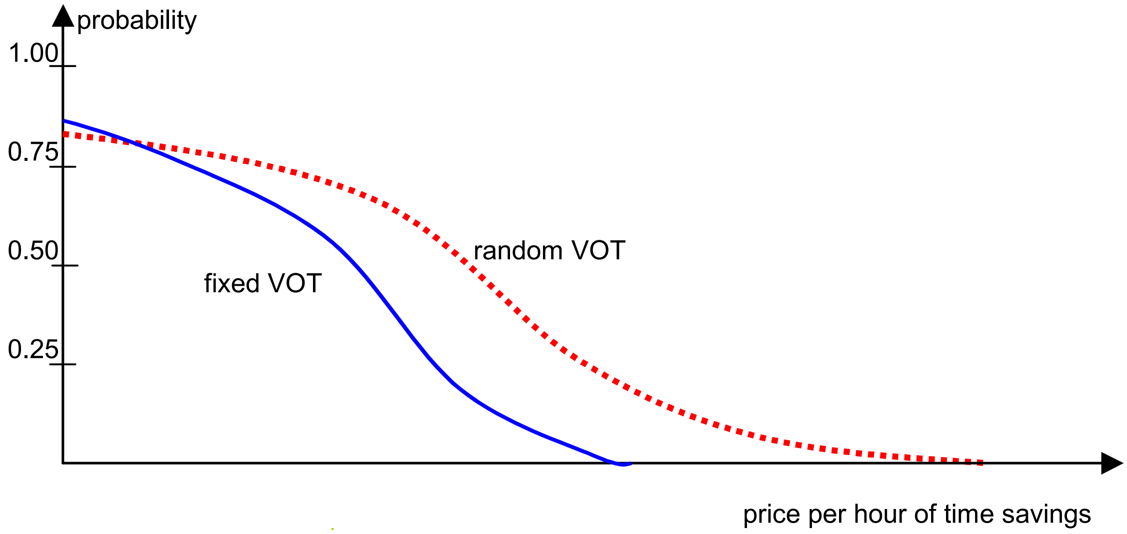
$$U = (t+\xi)\ T + cC + sS + \varepsilon \qquad (2)$$

where, ξ is standard deviation around t. The coefficients are usually estimated by applying error component (EC) models. These models are also often referred to as mixed logit models.

Travel time coefficients gets therefore a random distribution with a mean value t and standard deviation ξ. VOT becomes in this case distributed (random) instead of fixed. Figure 1 shows changes in probability of paying for certain time saving (say 30 minutes) from fixed VOT and log-normal in regard to price per hour of time savings (Ben-Akiva, Bolduc and Bradley, 1993). It should be noted that in this case the random VOT follows the log-normal distribution. The figure shows that:

- For a given travel cost, travel demand differs between the EC and the MNL models. Due to the longer tail, the EC models give higher demand than the MNL models for high travel costs.
- The demand slope is less steep in the EC models relative to the MNL models, i.e. their tail is much longer. That means that according to the EC models even for high travel costs there will be travel demand. This is the same as to say that the total demand for an alternative i is greater for the random VOT than for the fixed VOT.

Figure 1 – Probability of paying for certain time saving from fixed VOT and log-normal VOT in regard to price per hour of time savings



Distribution of t (and therefore VOT) can take different forms, as for instance normal and log-normal. Equation (2) can be extended in relation to income in two possible ways. Firstly, cost coefficient from (1) and (2) can be spilt into a number of coefficients set beside cost variables for respondents that belong to different income groups.

$$U = (t+\xi)\ T + c_1C^*I_1 + c_2C^*I_2 + sS + \varepsilon \qquad (3)$$

where, I_1 and I_2 are income-class dummy variables and c_1 and c_2 are cost coefficients for I_1 and I_2 respectively. We expect here that VOT is lower for lower income class. Equation (3) includes only two income classes while in reality we might have many more classes.

Secondly, a coefficient can be estimated for a ratio of travel costs and income according to (4):

$$U = (t+\xi)\ T + cC + q(C/I) + \varepsilon \qquad (4)$$

where, C/I gives a ratio of the travel costs and income. We expect in this case that q is negative because with higher income the importance of travel cots gets lower. Note that the coefficients on travel cost and time in the utility function is normally negative, since the more resistance towards travel, the less utility. Both t, c and q is accordingly á priori expected to be negative.

4. MODELLING RESULTS

4.1 MNL and EC modelling results

The best estimated MNL and EC models are presented in table 2. Models 1 and 2 are MNL models according to equation (1) while models 3, 4 and 5 are EC models according to different versions of equation (2). Model 1 includes one cost coefficient. Model 2 deals with three cost coefficients, i.e. one related to driving costs (in DKK), one related to driving distances reformulated into driving costs, and one related to road pricing. Models 3 to 5 include one or more error components in its structure. The only difference between model 2 and 3 is that a random error was defined in model 3, connected to all time and cost coefficients (i.e. a very hypothetical situation). A dramatic improvement is observed in model 3 (an improvement of 75 likelihood units), pointing out that lots of taste variation exists in the data. Further disaggregation of the error component in models 4 and 5 gave even better results as all proved to be significantly different from zero.

Table 2 – Estimation results from the best MNL and EC models

File	model 1		model 2		model 3		model 4		model 5	
Observations	3388		3388		3388		3388		3388	
Final log (L)	-1662,6		-1645,7		-1571,1		-1561,3		-1538,1	
D.O.F.	8		10		11		14		16	
Rho²(0)	0,292		0,299		0,331		0,335		0,345	
Rho²(c)	0,290		0,297		0,329		0,333		0,343	
drvcost	-0.300	(-14.1)	-0.405	(-11.0)	-2.010	(-4.4)	-2.350	(-3.3)	-4.45	(-2.9)
fftime	-0.187	(-16.0)	-0.184	(-15.1)	-0.976	(-4.3)	-0.997	(-3.4)	-1.50	(-2.9)
cngtime	-0.299	(-19.9)	-0.296	(-19.1)	-1.530	(-4.5)	-1.48	(-3.4)	-2.25	(-3.0)
rdprice	-0.350	(-16.0)	-0.358	(-15.7)	-2.08	(-4.3)	-2.38	(-3.0)	-3.09	(-2.9)
inpeak	0.612	(2.6)	0.614	(2.6)	1.52	(2.4)	1.67	(2.2)	2.64	(2.0)
offpeak	1.10	(3.4)	1.17	(3.6)	2.63	(2.4)	2.49	(2.2)	3.37	(2.0)
t_malep	-0.674	(-2.5)	-0.705	(-2.6)	-1.86	(-2.5)	-1.93	(-2.2)	-3.28	(-2.1)
asc51	0.188	(2.4)	0.189	(2.4)	0.355	(1.5)	0.329	(1.3)	0.436	(1.5)
costdst			-0.157	(-4.7)	-1.09	(-3.9)	-1.18	(-2.9)	-1.65	(-2.1)
costSP5			-0.346	(-9.4)	-1.96	(-4.0)	-2.38	(-2.9)	-2.59	(-2.8)
ercmp					-1.16	(-4.0)				
cost1_e							-2.00	(-2.7)	-6.21	(-2.7)
fftime_e							-1.12	(-3.1)	-1.74	(-2.7)
cngtime_e							0.904	(2.9)	1.16	(2.7)
cost4_e							-1.48	(-2.3)	-1.96	(-2.7)
cost2_e									7.33	(2.3)
cost3_e									0.924	(1.8)

where:
drvcost; driving cost coefficient in the SP1 and SP3.
fftime; free flow time coefficient.
cngtime; congested time coefficient.
rdprice; coefficient for road pricing in the SP5.

inpeak; dummy variable from TOD experiments (i.e. SP3 and SP4) saying that if you originally travelled in peak hour, then when presented with an out-of-peak alternative you might (or might not) prefer to switch. A positive value means that the original time of travel (which is peak) is preferred.

offpeak; dummy variable from TOD experiments (i.e. SP3 and SP4) saying that if you originally travelled in out-of-peak hour, then when presented with an peak alternative you might (or might not) prefer to switch. A positive value means that the original time of travel (which is out-of-peak) is preferred.

t_malep; in the TOD experiments (i.e. SP3 and SP4), men who travel originally in the peak are more willing to stay in the peak than women.

asc51; alternative specific constant in the SP5 placed on the left side alternative (i.e. the original route). The positive value means that, when everything else is equal, the respondents prefer their original route, which is to be expected to happen.

costdst; cost coefficient calculated via distances in the SP2 and SP4.

costSP5; cost coefficient in the SP5.

ercmp; error component coefficient applied only in model 3. The coefficient was applied in all cost and time coefficients in all 5 experiments. The purpose of model 3 was to discover that the error component improve significantly the model estimations, i.e. see the final likelihood value in model 3 relative to models 2 and 1.

cost1_e; cost error component coefficient applied:

- in all cost coefficients in model 4, and
- in cost coefficients in the SP1 and SP3 in model 5.

fftime_e; free flow error component coefficient applied in all SP experiments.

cngtime_e; congested time error component coefficient applied in all SP experiments.

cost4_e; road pricing error component cost coefficient found in models 4 and 5.

cost2_e; error component cost coefficient found in model 5 applied only in the SP5.

cost3_e; error component cost coefficient (where costs are calculated on distances) found in model 5. It is applied in the SP2 and SP4.

The models are based on 3,388 SP observations after exclusion of those observations where the observed travel costs/distances were zero. The respondents' travel behaviour is well captured in the models, as the vast majority of the coefficients are estimated to be significantly different from zero for the 95% confidence interval. The best model estimated is model 5 where error components were placed behind different cost coefficients, free flow travel time and congested travel time, i.e. six error components in total.

The obtained VOT in model 5 are presented in table 3. The VOT are calculated simply by dividing the means of the normally distributed time and cost coefficients. This is theoretically wrong because the mean value of the random variable obtained by the ratio of two normally distributed random variables is Cauchy distributed. The problem here is that the mean and standard deviation of the Cauchy distribution are undefined (refer to Nielsen & Jovicic, 2003 for a further discussion on this issue).

Table 3 – VOT in DKK/hour in model 5 (EC model)

	SP1 and SP3	SP2 and SP4	SP5
Free flow travel time	20.2	54.5	34.7
Congested travel time	30.3	81.8	52.1

When driving costs are presented in DKK (SP1, SP3 and SP5) then lower VOT are obtained than when distances are presented in the experiments (SP2 and SP4). A possible explanation to this is that the drivers are more aware of travel distances than driving costs. The respondents then in the cost experiment state their thought willingness to pay, while they in real life primarily want to minimise time, and the length/time experiment describe this better. There is a large disagreement between the respondents regarding km-costs with respect to what components are included it, i.e. most drivers take into account only petrol costs, some drivers include maintenance and oil, while few include also insurance costs in the km-costs. Due to that, more sensitivity towards driving costs is paid in the SP1 and SP3 relative to travel times, while the opposite is true in distance experiments (SP2 and SP4).

In the SP5, driving costs were presented together with road pricing. As we estimated higher VOT for this experiment than in the SP1 and SP3, we conclude that value of travel time raises when other costs are also presented in the choice experiment. The respondents experienced road pricing as being 19% more negative than driving costs. This is probably due to the annoyance connected to the additional travel costs. In all three cases the congested travel time is weighed more negatively than free flow travel time, as we could expect.

If the taste variation among the respondents is not modelled then significantly different VOT are obtained. Table 4 shows the VOT achieved in model 2, which is a MNL model. Percentage difference between the VOT in models 2 and 5 are given in parentheses. It can be noticed in the table that differences can be as large as 45%. If we focus on VOT obtained from SP1 and SP3, where travel costs are presented to the respondents, then we notice that omitting taste variation in the model estimation relates to some 40% higher VOT.

Table 4 - VOT in DKK/hour in model 2 (MNL model)

	SP1 and SP3	SP2 and SP4	SP5
Free flow travel time	27.3 (+35%)	70.3 (+29%)	31.9 (-8%)
Congested travel time	43.9 (+45%)	113.1 (+38%)	51.3 (-1%)

4.2 EC model with normally distributed VOT

A model is estimated where time components are normally distributed while the cost components are kept as constants. The ratio of the normally distributed time coefficient and cost constant is a normally distributed VOT with the mean value equal to the ratio of the time component mean value and the cost constant.

The final likelihood in the model is –1601.09, which is somewhat in between the models 2 and 3 in table 2. This means that substantial taste variation is found in the time variables, which improves substantially the best MNL model. However, even larger taste variation is found in the cost variables, which are omitted here due to the theoretical considerations. Table 5 shows the VOT achieved in this model.

While the best EC model from table 2 (i.e. model 5) has lower VOT in the SP1 and SP3 than the best MNL model (i.e. model 2), this model has higher VOT than model 2. This proves that the VOT from the EC models can be found on both sides of the VOT from the MNL models.

Table 5 - VOT in DKK/hour in the EC model with time variables' normal distribution

	SP1 and SP3	SP2 and SP4	SP5
Free flow travel time	32.0	64.1	37.3
Congested travel time	50.7	101.6	56.1

While the best EC model from table 2 (i.e. model 5) has lower VOT in the SP1 and SP3 than the best MNL model (i.e. model 2), this model has higher VOT than model 2. This proves that the VOT from the EC models can be found on both sides of the VOT from the MNL models.

4.3 Income effect modelling results

Income effect is modelled in the AKTA project according to equations (3) and (4). The more traditional way of modelling income effect is by splitting the sample by income classes, equation (3). The respondents have reported in the survey their gross income for 2001 in the form of belonging to income classes. There were defined nine income classes:

1. < DKK 50.000
2. DKK 50 - 100.000
3. DKK 100 - 200.000
4. DKK 200 - 300.000
5. DKK 300 - 400.000
6. DKK 400 - 500.000
7. DKK 500 - 750.000
8. DKK 750 – 1.000.000
9. > DKK 1.000.000

Data allowed us to estimate only two cost coefficients; one for income groups up to DKK 400.000 and the other for income above DKK 400.000. 70% of the sample (195 respondents) belongs to the first income group while 30% (84 respondents) belong to the higher income group. The income effect could not be estimated reasonably in the SP2 and SP4 experiments where travel distances were presented to the respondents, i.e. it turned out that lower income group respondents have higher VOT than those with high income. All coefficients that are estimated in the EC model according to equation (3) are significantly different from zero. We present therefore the estimation results of this model in form of VOT in table 6. In each cell to the left is given VOT for lower income group, to the right is given VOT for higher income group while in parentheses are given VOT from table 1 (EC model). As expected, those respondents with lower income have also lower VOT than those respondents with high income. It can be also noticed that the mean VOT (figures in the parentheses) are closer to the lower income respondents than to those with high income. The reasons for that are that the low-income sample is greater than the high-income sample, and that the distribution of the high-income respondents across income groups is more uniform than in the case of low-income travellers.

The last model type estimated in the study is a model according to equation (4). "q" coefficient was estimated to be +3.9 with a t-value of 1.0. That is to say that the income effect could not be captured correctly in the model according to formula (4) due to the wrong sign of q. Coefficient q is also not significantly different from zero (low t-value) because of what the obtained VOT in this model are very similar to those VOT from model 5 (table 2).

Table 6 - VOT in DKK/hour in income model according to equation (3)

	SP1 and SP3	SP2 and SP4	SP5
Free flow travel time	18.9 / 22.8 (20.2)	54.5	32.1 / 44.8 (34.7)
Congested travel time	28.4 / 34.3 (30.3)	81.8	48.2 / 67.2 (52.1)

The last model type estimated in the study is a model according to equation (4). “q” coefficient was estimated to be +3.9 with a t-value of 1.0. That is to say that the income effect could not be captured correctly in the model according to formula (4) due to the wrong sign of q. Coefficient q is also not significantly different from zero (low t-value) because of what the obtained VOT in this model are very similar to those VOT from model 5 (table 2).

5. DISCUSSION AND CONCLUSIONS

Values of travel time (VOT) in the AKTA project proved to be sensitive to the type of design of SP experiments, i.e. different VOT are obtained when driving distance is presented to the respondent instead of driving costs. We conclude therefore that methodological effect exists in SP analysis and that respondents react differently in the hypothetical situations depending on the prior knowledge to the variables chosen in the SP design.

VOT also proved to be influenced by the presence of other cost components in the same experiment. VOT in SP5 experiment is higher than VOT from SP1 experiment because both driving costs and road pricing are presented to the respondents in SP5 experiment. For the further research it could be interested to measure the effect of one total-cost variable that is dependent of two varying cost components, i.e. driving costs and road pricing.

VOT is dependent of the modelling methodology. There are at least two theoretical advantages of the EC models relative to the MNL models:

- EC models give better fit to data because taste variation within the sample is captured.
- The demand slope is less steep in the EC models relative to the MNL models, i.e. their tail is longer.

All EC models in the project have more positive final likelihood values than the best MNL model (model 2 from table 2) and therefore better fit to the data. Further improvement in the model estimations is obtained by including income effect. That was done in two ways, i.e. by splitting the cost coefficient between two income groups and by estimating en extra coefficient for the ratio of driving costs and income. The best results are obtained in the first type of models, where lower-income group travellers (i.e. respondents with the maximum annual gross income of DKK 400.000) have lower VOT than higher-income travellers (i.e. respondents with the minimum annual gross income of DKK 400.000). If, for instance, road pricing is introduced then, according to the model, the lower-income travellers are more influenced than higher-income travellers (as we could expect). This model is the best estimated model in the project.

Finally, the coefficient beside the ratio of driving costs and income (coefficient q in equation (4)) proves to be of the wrong (positive) sign and with low significance. The conclusion here is that variation of the cost coefficient (and therefore variation of VOT) cannot be entirely explained by the income effect.

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