FACULTY OF SOCIAL SCIENCES
UNIVERSITY OF COPENHAGEN

PhD thesis

Katrine Hjorth

Essays in Transport Economics:

Using stated preference data in the valuation of non-market goods

Academic advisors: Mette Ejrnæs and Mogens Fosgerau

Submitted: January 2011

Essays in Transport Economics: Using stated preference data in the valuation of non-market goods

Katrine Hjorth

PhD thesis submitted to the Department of Economics,
Faculty of Social Sciences, University of Copenhagen

January 2011

Summary

This thesis consists of four papers investigating different aspects of the use of stated preference data in the valuation of non-market goods.

Stated preference (SP) data are answers to hypothetical questions or choices, whereby respondents implicitly or explicitly state their preferences for one or more goods. One of the uses of SP data is to estimate the values of non-market goods. In the applications in this thesis, the non-market goods are travel time and travel time variability; the latter denoting the randomness in travel time a traveller faces when deciding when, where, and how to travel.

An overall topic in three of the four papers is that preferences measured from SP data may be *reference-dependent*, a concept from prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991) meaning that the carriers of value are gains and losses relative to a reference point. According to prospect theory, preferences are reference-dependent and exhibit *loss aversion* (losses are valued more heavily than gains) and *diminishing sensitivity* with respect to the size of gains and losses.

In Chapter 2, *Between-mode-differences in the value of travel time: Self-selection or strategic behaviour?* (joint work with Mogens Fosgerau and Stéphanie Vincent Lyk-Jensen) [1], we use SP data to measure the value of travel time (VTT) for three transport modes and investigate the differences between modes. Many VTT studies (Mackie et al., 2003; Fosgerau et al., 2007) find that car users have a higher VTT than public transport users, contrary to the theoretical prediction that a given individual should be willing to pay more to save travel time in a public transport mode than in his own car, since travel time in a public transport mode is considered less comfortable. Taken at face value, the high VTT for car drivers would lead to a preference for transport investments benefitting car traffic. However, it is likely that the pattern is at least partly due to self-selection: that people with a high VTT to a higher degree choose the car over public transport.

Our results show that the difference between car and public transport should not be interpreted as if a given individual would benefit more from reduced car travel times compared to bus or train travel times. Rather, it turns out that a large part of the variation in the VTT across modes can be explained by differences in the types of users. The direction of the effects is consistent with the self-selection hypothesis. Once user type effects are controlled for, we are able to observe the underlying mode effects, that are consistent with the differences in comfort.

In Chapter 3, *Using prospect theory to investigate the low value of travel time for small time changes* (joint work with Mogens Fosgerau) we investigate prospect theory as a possible explanation to a phenomenon often encountered in SP studies measuring the VTT: that the measured marginal VTT increases with the size of the time change considered, in conflict with standard neoclassical theory (Gunn, 2001; Hultkrantz and Mortazavi, 2001; Mackie et al., 2001, 2003; Fosgerau et al., 2007). This effect is large enough to be of considerable economic significance, and problematic because it would not be appropriate for evaluations of transport projects to apply a lower unit VTT for

[1] Published in *Transportation Research Part D: Transport and Environment*, vol. 15(7), 2010; doi: 10.1016/j.trd.2010.04.005.

small time changes (Fosgerau et al., 2007).

Recently, De Borger and Fosgerau (2008) suggested that the phenomenon is generated by preferences being reference-dependent and exhibiting diminishing sensitivity for gains and losses, with a stronger degree of diminishing sensitivity for money than for travel time. Our paper extends their analysis, using data that provide better identification of the relevant parameters, and presents an empirical test with potential to falsify the prospect theory explanation. Our results show that behaviour is consistent with prospect theory, and that diminishing sensitivity is stronger for money than for travel time, supporting prospect theory as an explanation of the phenomenon that the marginal VTT increases with the size of the time change.

In Chapter 4, *Loss aversion and individual characteristics* (joint work with Mogens Fosgerau) [2], we investigate how loss aversion with respect to travel time and money varies with individual characteristics and features of the experimental design, in an SP experiment where respondents make trade-offs between travel time and travel cost. To the best of our knowledge, we are the first to analyse heterogeneity in loss aversion separately in two dimensions. In this way we are able to provide new evidence on factors that determine the degree of loss aversion in SP data with trade-offs between two goods.

We find a higher degree of loss aversion in the travel time dimension than in the cost dimension, i.e. the overweighting of losses relative to gains is larger for travel time than for money. The degree of loss aversion in the travel time dimension increases with the respondents' age and decreases with their level of education. Further, our results suggest that people tend to be more loss averse when the reference is well established: the respondents exhibit more loss aversion in an experiment, where the reference point is assumed to be a recently made trip, than in an experiment where the reference is assumed to be a similar (potentially hypothetical) trip with another transport mode. This effect is particularly strong if the respondent rarely makes such a trip.

In Chapter 5, *Cumulative prospect theory applied to stated preference data with travel time variability*, I analyse data from a standard SP experiment used to measure preferences for travel time variability: choices between travel alternatives that are characterized by a monetary cost and a discrete travel time distribution with five possible outcomes. I use a behavioural model based on cumulative prospect theory (Tversky and Kahneman, 1992), which accommodates both reference-dependence and rank-dependent probability weighting, i.e. that the weight a respondent attaches to a travel time outcome is not proportional to its probability.

The results show that the respondents' behaviour is consistent with the behavioural premises from cumulative prospect theory, and indicate significant probability weighting: respondents tend to overweight the likelihood of the extreme outcomes (the largest gain, the smallest gain, the smallest loss, and the largest loss). This result has consequences for the design of SP experiments about travel time variability, since the results from such experiments cannot be applied in forecasts and welfare analyses, if respondents weight travel time outcomes differently from what the experimenter intends.

[2]Accepted for publication in *Environmental and Resource Economics*, vol. 49(4), 2011; doi: 10.1007/s10640-010-9455-5.

References

De Borger, B., Fosgerau, M., 2008. The trade-off between money and travel time: A test of the theory of reference-dependent preferences. Journal of Urban Economics 64, 101–115. [ii]

Fosgerau, M., Hjorth, K., Lyk-Jensen, S. V., 2007. The Danish Value of Time Study: Final report. Report for the Danish Ministry of Transport, Danish Transport Research Institute. [i, ii]

Gunn, H., 2001. Spatial and temporal transferability of relationships between travel demand, trip cost and travel time. Transportation Research, Part E 37, 163–189. [i]

Hultkrantz, L., Mortazavi, R., 2001. Anomalies in the value of travel-time changes. Journal of Transport Economics and Policy 35, 285–300. [i]

Kahneman, D., Tversky, A., 1979. Prospect theory: An analysis of decision under risk. Econometrica 47, 263–291. [i]

Mackie, P., Fowkes, A., Wardman, M., Whelan, G., Nellthorp, J., Bates, J., 2003. Values of travel time savings in the UK – Report to Department for Transport. Institute for Transport Studies, University of Leeds, in association with John Bates Services. [i]

Mackie, P., Jara-Díaz, S., Fowkes, A., 2001. The value of travel time savings in evaluation. Transportation Research, Part E 37, 91–106. [i]

Tversky, A., Kahneman, D., 1991. Loss aversion in riskless choice: A reference-dependent model. The Quarterly Journal of Economics 106 (4), 1039–1061. [i]

Tversky, A., Kahneman, D., 1992. Advances in prospect theory: Cumulative representation of uncertainty. Journal of Risk and Uncertainty 5, 297–323. [ii]

Dansk resumé

Denne afhandling består af fire artikler, som undersøger forskellige aspekter vedrørende anvendelsen af *stated preference* data til værdisætning af ikke-markedsvarer.

Stated preference (SP) data er svar på hypotetiske spørgsmål eller valg, hvormed respondenter implicit eller eksplicit angiver deres præferencer for et eller flere goder. Én af anvendelserne af SP data er til estimation af værdien af ikke-markedsvarer. I denne afhandling er ikke-markedsvarerne rejsetid og rejsetidsvariabilitet; sidstnævnte betegner den grad af tilfældighed i rejsetid, en rejsende står over for, når han beslutter hvornår, hvor og hvordan han skal rejse.

Et gennemgående emne i tre af de fire artikler er, at præferencer målt fra SP data kan være *referenceafhængige* – et begreb fra *prospect theory* (Kahneman og Tversky, 1979; Tversky og Kahneman, 1991) med den betydning, at værdien af en given vare afhænger af, hvorvidt den opfattes som en gevinst eller et tab i forhold til individets referencepunkt. Ifølge prospect theory er præferencer referenceafhængige og udviser *tabs-aversion* (tab vægtes højere end gevinster) og *aftagende følsomhed* overfor størrelsen af gevinster og tab.

I kapitel 2, *Between-mode-differences in the value of travel time: Self-selection or strategic behaviour?* (skrevet i samarbejde med Mogens Fosgerau og Stéphanie Vincent Lyk-Jensen) [3], bruger vi SP data til at måle værdien af rejsetid (*value of travel time*, VTT) for tre transportmidler og undersøger forskellene mellem transportmidlerne. Mange VTT studier (Mackie et al., 2003; Fosgerau et al., 2007) finder, at bilister har højere VTT end brugere af kollektiv transport, modsat den teoretiske forventning at et givet individ burde være villig til at betale mere for at spare rejsetid i et kollektivt transportmiddel end i sin egen bil, siden rejsetiden i det kollektive transportmiddel betragtes som mindre komfortabel. Tages resultatet for pålydende, ville det medføre en prioritering af de transportinvesteringer, der gavner den private biltrafik. Resultatet skyldes dog formentlig til dels selv-selektion: At folk med høj VTT i højere grad anvender bil end kollektiv transport.

Vores resultater viser, at forskellen mellem bil og kollektiv transport ikke bør fortolkes, som om et givet individ ville have større nytte af reducerede bilrejsetider end af reducerede bus- eller togrejsetider. Derimod viser det sig, at en stor del af variationen i VTT kan forklares med forskellen i typen af brugere. Denne effekt er i overensstemmelse med antagelsen om selv-selektion. Efter at have kontrolleret for forskelle i brugertyper, kan vi observere de underliggende transportmiddeleffekter, som viser sig at være i overensstemmelse med komfortforskellene.

I kapitel 3, *Using prospect theory to investigate the low value of travel time for small time changes* (skrevet i samarbejde med Mogens Fosgerau), undersøges det, om prospect theory kan forklare et velkendt fænomen i SP studier, der måler VTT: At den målte værdi af et minuts rejsetid vokser med størrelsen af den betragtede rejsetidsændring, i konflikt med almindelig neoklassisk teori (Gunn, 2001; Hultkrantz og Mortazavi, 2001; Mackie et al., 2001, 2003; Fosgerau et al., 2007). Effekten er stor nok til at være af betragtelig økonomisk betydning og problematisk, fordi det ville være inkon-

[3]Publiceret i *Transportation Research Part D: Transport and Environment*, vol. 15(7), 2010; doi: 10.1016/j.trd.2010.04.005.

sistent at anvende en lavere enhedsværdi for små rejsetidsbesparelser i den samfundsøkonomiske analyse af transportinvesteringer (Fosgerau et al., 2007).

For nyligt har De Borger og Fosgerau (2008) foreslået, at fænomenet opstår, fordi respondenterne har referenceafhængige præferencer, som udviser aftagende følsomhed for størrelsen af gevinster og tab, og hvor følsomheden for prisændringer aftager hurtigere end for rejsetidsændringer. Vores artikel udvider deres analyse ved at bruge data, som tillader en bedre identifikation af de relevante parametre, og præsenterer en empirisk test, der kan falsificere denne forklaring. Vores resultater viser, at respondenterne opfører sig i overensstemmelse med prospect theory, og at følsomheden for prisændringer aftager hurtigere end for rejsetidsændringer. De støtter således antagelsen om, at prospect theory kan forklare fænomenet med, at VTT afhænger af rejsetidsændringens størrelse.

I kapitel 4, *Loss aversion and individual characteristics* (skrevet i samarbejde med Mogens Fosgerau) [4], undersøger vi, hvordan tabs-aversion med hensyn til rejsetid og penge afhænger af individkarakteristika og egenskaber ved det eksperimentelle design i et SP eksperiment, hvor respondenter foretager trade-offs mellem rejsetid og penge. Så vidt vides, er vi de første til at analysere heterogenitet i tabs-aversion separat i to dimensioner. Vi frembringer dermed ny viden om, hvilke faktorer der bestemmer graden af tabs-aversion i SP data med trade-offs mellem to varer.

Vi finder en større grad af tabs-aversion i rejsetidsdimensionen end i pengedimensionen, dvs. overvægtningen af tab i forhold til gevinster er større for rejsetid end for penge. Graden af tabs-aversion i rejsetidsdimensionen stiger med respondenternes alder og aftager med deres uddannelsesniveau. Desuden afslører vores resultater en tendens til, at graden af tabs-aversion er højere, når referencen er bedre etableret: Respondenterne udviser mere tabs-aversion i et eksperiment, hvor referencepunktet antages at være en nyligt foretaget rejse, end i et eksperiment, hvor referencepunktet antages at være en tilsvarende (potentielt hypotetisk) rejse med et andet transportmiddel. Dette gælder i særlig grad, hvis respondenten sjældent foretager en sådan rejse.

I kapitel 5, *Cumulative prospect theory applied to stated preference data with travel time variability*, analyseres data fra en type af SP eksperimenter ofte anvendt til at måle præferencer for rejsetidsvariabilitet: valg mellem rejsealternativer kendetegnet ved en pris og en diskret rejsetidsfordeling med fem mulige udfald. Til at modellere respondenternes opførsel anvendes en model baseret på *cumulative prospect theory* (Tversky og Kahneman, 1992), som tager højde for referenceafhængighed og sandsynlighedsvægtning, dvs. at den vægt, respondenterne tillægger et rejsetidsudfald, ikke er proportional med udfaldets sandsynlighed.

Resultaterne viser, at respondenterne opfører sig i overensstemmelse med cumulative prospect theory, og indikerer signifikant sandsynlighedsvægtning: Respondenterne har en tendens til at lægge for stor vægt på de ekstreme udfald (den største gevinst, den mindste gevinst, det mindste tab og det største tab). Resultaterne har betydning for den måde, SP studier om rejsetidsvariabilitet designes på, idet resultater fra sådanne studier ikke kan anvendes i prognoser og samfundsøkonomiske analyser, hvis respondenterne tillægger rejsetidsudfaldene en anden vægt end den tiltænkte.

[4] Accepteret til publikation i *Environmental and Resource Economics*, vol. 49(4), 2011; doi: 10.1007/s10640-010-9455-5.

References

De Borger, B., Fosgerau, M., 2008. The trade-off between money and travel time: A test of the theory of reference-dependent preferences. Journal of Urban Economics 64, 101–115. [v]

Fosgerau, M., Hjorth, K., Lyk-Jensen, S. V., 2007. The Danish Value of Time Study: Final report. Report for the Danish Ministry of Transport, Danish Transport Research Institute. [iv, v]

Gunn, H., 2001. Spatial and temporal transferability of relationships between travel demand, trip cost and travel time. Transportation Research, Part E 37, 163–189. [iv]

Hultkrantz, L., Mortazavi, R., 2001. Anomalies in the value of travel-time changes. Journal of Transport Economics and Policy 35, 285–300. [iv]

Kahneman, D., Tversky, A., 1979. Prospect theory: An analysis of decision under risk. Econometrica 47, 263–291. [iv]

Mackie, P., Fowkes, A., Wardman, M., Whelan, G., Nellthorp, J., Bates, J., 2003. Values of travel time savings in the UK – Report to Department for Transport. Institute for Transport Studies, University of Leeds, in association with John Bates Services. [iv]

Mackie, P., Jara-Díaz, S., Fowkes, A., 2001. The value of travel time savings in evaluation. Transportation Research, Part E 37, 91–106. [iv]

Tversky, A., Kahneman, D., 1991. Loss aversion in riskless choice: A reference-dependent model. The Quarterly Journal of Economics 106 (4), 1039–1061. [iv]

Tversky, A., Kahneman, D., 1992. Advances in prospect theory: Cumulative representation of uncertainty. Journal of Risk and Uncertainty 5, 297–323. [v]

Contents

Acknowledgements

This thesis was written from February 2008 to January 2011, during my years as a PhD student at the Department of Economics, University of Copenhagen, and at the Department of Transport, Technical University of Denmark (DTU Transport). I gratefully acknowledge the financial support of the Danish Social Science Research Council (FSE) and DTU Transport. Moreover, I am grateful to DTU Transport and the Institute of Transport Economics in Oslo for permission to use their data.

I would like to thank my supervisors Mette Ejrnæs and Mogens Fosgerau for their advice and support, not least for patiently reading and commenting on countless revisions of my papers. I owe a special thanks to Mogens, who is also co-author on three of the four papers in this thesis, for always taking a great interest in my work and for being an inexhaustible source of ideas. I have learned a lot from him, both during my PhD, and during my work as a research assistant at DTU Transport. Thanks also to my former colleague Stéphanie Vincent Lyk-Jensen, who is co-author on one of the papers: I enjoyed the time we worked together. Thanks to Stefan Mabit, Ninette Pilegaard, Ken Small, Farideh Ramjerdi, Stefan Flügel, and Paul Koster, for commenting on my work and discussing ideas. Stefan Flügel also deserves thanks for patiently answering all my questions about the Norwegian data.

During my PhD, I had the pleasure of visiting the Department of Spatial Economics at the VU University Amsterdam. I am grateful to Erik Verhoef for arranging my visit, and to him, Paul Koster, Yin-Yen Tseng, Stefanie Peer, and Jasper Knockaert for taking time to discuss my work. I am thankful to everybody at the Department for making me feel welcome, and I thank the Department for providing me with a daily work space and helping me find accommodation in Amsterdam.

I would like to thank everybody at DTU Transport, my office-mate Ismir Mulalic in particular, for a very nice place to work, with dedicated colleagues and a friendly atmosphere. I am grateful to the Department for the support I have received, not just during my PhD, but also during the writing of my Master's thesis.

A special thanks to my cousin Bo for always taking an interest in my studies, for somehow convincing me that econometrics is fun, and for checking up on me during my PhD. Finally, I owe thanks to all my family – in particular my parents Anne-Marie and Søren, my brother Kristian, and my husband Kim – for their understanding and support throughout my life and my studies.

Katrine Hjorth
Copenhagen, January 2011

Chapter 1

Introduction and Summary

This thesis consists of four papers investigating different aspects of the use of stated preference data in the valuation of non-market goods. The papers are self-contained and can be read independently of each other.

Stated preference (SP) data are answers to hypothetical questions or choices, whereby respondents implicitly or explicitly state their preferences for one or more goods. SP data are used to forecast behaviour in hypothetical scenarios (e.g., putting a new product on the market), and to estimate the values of non-market goods. In the applications in this thesis, the non-market goods are travel time and travel time variability; the latter denoting the randomness in travel time a traveller faces when deciding when, where, and how to travel. Travelling is considered to be an activity undertaken not for its own sake, but to enable the undertaking of other activities, such as work or leisure activities, and so both travel time and travel time variability are assumed to have a negative effect on the traveller's utility. The data stem from national Danish and Norwegian valuation studies, conducted to establish values of travel time and travel time variability for use in welfare-economic evaluations of transport infrastructure policies (Fosgerau et al., 2007; Samstad et al., 2010). Such values are important because reductions in average travel time and travel time variability often constitute the main part of the benefits of infrastructure investments.

Some of the topics covered in this thesis are specific to transport economics; in other cases, the topics and the methodology are more general and could also apply to fields as health economics or environmental economics.

An overall topic in three of the four papers is that preferences measured from SP data may be *reference-dependent*, a concept from prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991) meaning that the carriers of value are gains and losses relative to a reference point. Prospect theory defines preferences in terms of value functions that exhibit *loss aversion* (losses are valued more heavily than gains) and *diminishing sensitivity* with respect to the size of gains and losses.

Descriptive behavioural theories as prospect theory, rank-dependent utility theory (Quiggin, 1982) and cumulative prospect theory (Tversky and Kahneman, 1992), have only recently been applied in travel behaviour research (see, e.g. Van de Kaa, 2008; Avineri and Bovy, 2008). Van de Kaa (2005) was one of the first to argue that SP studies measuring the value of travel time (VTT) should control for reference-dependence, preceded by a discussion in the transport literature of the gap between willingness-to-pay (WTP, the maximum amount the traveller is willing to pay to reduce travel time by one minute) and willingness-to-accept (WTA, the minimum amount a traveller would accept in return for a one-minute increase in travel time). Recent VTT studies have allowed for reference-dependence in the form of loss aversion, whereas diminishing sensitivity for gains and losses is generally not accommodated (Fosgerau et al., 2007; Ramjerdi et al., 2010). In the case of travel time variability, valuation studies appear to ignore reference-dependence. They commonly assume that respondents' choices maximise their expected utility, though a few studies apply rank-dependent utility models that accommodate probability weighting – i.e. that the weight a respondent attaches to a travel time outcome is not proportional to its probability (Michea and Polak, 2006; de Lapparent and Ben-Akiva, 2011; Hensher and Li, 2011).

The paper in Chapter 2, *Between-mode-differences in the value of travel time: Self-selection or strategic behaviour?* (published in *Transportation Research Part D: Transport and Environment*[1]) is joint work with Mogens Fosgerau and Stéphanie Vincent Lyk-Jensen. In the paper, we use SP data to measure the VTT for three transport modes and investigate the differences between modes. Many VTT studies (Mackie et al., 2003; Fosgerau et al., 2007) find that car users have a higher VTT than public transport users, contrary to the theoretical prediction that a given individual should be willing to pay more to save travel time in a public transport mode than in his own car, since travel time in a public transport mode is considered less comfortable. A likely explanation is self-selection: that people with a high VTT to a higher degree choose the car over public transport. Another potential explanation is that car drivers and public transport users interpret the SP experiment differently, such that car drivers to a higher degree see the experiment as an opportunity to express a wish for increased speed, whereas the public transport users see the experiment as an opportunity to influence the setting of fares. This would give them an incentive to act strategically: car drivers to overstate their VTT, and public transport users to understate their VTT.

To investigate the differences between modes, we measure respondents' VTT not only in their current mode, but also in an alternative mode that could have been used if the current mode was unavailable. Consequently, we observe the same individual's VTT in different modes, and can thereby disentangle mode effects (the variation in the VTT across transport modes for a given individual) from user type effects (the variation in the VTT in a given transport mode between the users of different modes).

We use a mixed logit framework to model respondents' responses as a function of their VTT, and estimate separate VTT distributions for each 'user type' (defined by current and alternative mode), and for each mode in which this user type is observed. Our results indicate that user type effects in a direction consistent with self-selection are a main driver behind the variation in the VTT across modes: Current car users generally have higher VTT, no matter which mode we measure their VTT in, and current bus users have the lowest VTT. Once user type effects are controlled for, we are able to observe the underlying mode effects. For the respondent groups having the lowest VTT (current bus users and respondents who would use the bus as alternative) no significant mode

[1]Vol. 15(7), 2010; doi: 10.1016/j.trd.2010.04.005.

effects can be found. Among the remaining groups, the VTT is significantly lower in car than in train, which is consistent with the differences in comfort (the car being more comfortable). We find no evidence of strategic behaviour.

Our results have important implications: Taken at face value, the high VTT for car drivers would lead to a preference for transport investments benefitting car traffic. However, we show that the difference between car and public transport should not be interpreted as if a given individual would benefit more from reduced car travel times compared to bus or train travel times. This needs to be taken into account when comparing travel time savings in private cars for one group of individuals to time savings in public transport for another group: such a comparison should acknowledge the redistributive implications of prioritizing one transport investment over another. In Danish practice, a single appraisal value of travel time is used for all transport modes to correct for the empirical differences and secure a fair comparison of road projects and public transport projects (Fosgerau et al., 2007).

Chapter 3 is the paper *Using prospect theory to investigate the low value of travel time for small time changes* (joint work with Mogens Fosgerau). As the title suggests, the paper investigates prospect theory as a possible explanation to a phenomenon often encountered in SP studies measuring the VTT: that the measured marginal VTT increases with the size of the time change considered, in conflict with standard neoclassical theory (Gunn, 2001; Hultkrantz and Mortazavi, 2001; Mackie et al., 2001, 2003; Fosgerau et al., 2007). This effect is large enough to be of considerable economic significance[2], and problematic because it would be inappropriate for evaluations of transport projects to apply a lower unit VTT for small time changes (Fosgerau et al., 2007).

Recently, De Borger and Fosgerau (2008) suggested that the phenomenon is generated by preferences being reference-dependent and exhibiting diminishing sensitivity for gains and losses, with a stronger degree of diminishing sensitivity for money than for travel time. For this explanation to be valid, two conditions must hold: First, the reference-dependent model underlying the analysis in De Borger and Fosgerau (2008) must be an adequate description of the behaviour observed in the SP surveys. Second, the observed preferences should exhibit stronger diminishing sensitivity for money than for travel time. De Borger and Fosgerau (2008) provide empirical support for the latter condition, but only partly for the former, because they lack the data to separately identify the degrees of diminishing sensitivity for travel time and cost. Our paper extends their analysis, using data that provide better identification of the relevant parameters, and thus presents an empirical test with potential to falsify the prospect theory explanation.

De Borger and Fosgerau (2008)'s analysis is based on SP data with choices between a fast and expensive travel alternative and a slower and cheaper one, where time and cost attributes are varied around individual-specific reference values to generate gains and losses in both dimensions, but always keeping one time attribute and one cost attribute equal to the reference.[3] Our paper extends their analysis by also using non-reference-based choices where the time attributes of both alternatives are different from the reference time. Using the modelling framework from De Borger and Fos-

[2]See Table 4 in Mackie et al. (2003) and Table 5 in Fosgerau et al. (2007)

[3]Such data are used in many European VTT studies, cf. Burge et al. (2004); Fosgerau et al. (2007); de Jong et al. (2007); Ramjerdi et al. (2010).

gerau (2008), we formulate a discrete choice model, in which choice depends on the reference-free marginal value of travel time and reference-dependent value functions for time and money. We test this parametric model by comparing its predicted equiprobability curves to those of the data, estimated using a semi-parametric local logit estimator. Based on this test, we conclude that our data does not reject the parametric model. The value functions are estimated from the parametric model using mixed logit estimation. Our results are consistent with prospect theory, and show a stronger diminishing sensitivity for money than for travel time, supporting prospect theory as an explanation of the phenomenon that the marginal VTT increases with the size of the time change.

The paper in Chapter 4, *Loss aversion and individual characteristics* (joint work with Mogens Fosgerau) is accepted for publication in *Environmental and Resource Economics*[4]. Here, we investigate how loss aversion with respect to travel time and money varies with individual characteristics and features of the experimental design, in an SP experiment where respondents make trade-offs between travel time and travel cost.

Several studies have investigated the extent of heterogeneity in loss aversion, either by measuring at the individual level or by comparing averages over groups of respondents. Some studies work with preferences for a single good (money), others in a two-good scenario (most often money and a non-monetary good), measuring trade-offs between the two goods. However, none of these studies measures loss aversion separately in the money dimension and the good dimension, as can be done by considering both gains and losses in both dimensions; see e.g. Bateman et al. (1997).

In our paper we estimate loss aversion at the individual level and separately in the time and money dimensions. In this way we are able to provide new evidence on factors that determine the degree of loss aversion. In particular, we are able to examine how loss aversion in time and money correlates with gender, age, income etc. as well as with aspects of the choice context.

We apply a fixed effects logit estimator, which allows us to identify the parameters of interest under weak assumptions. We find a higher degree of loss aversion in the travel time dimension than in the cost dimension, i.e. the overweighting of losses relative to gains is larger for travel time than for money. The degree of loss aversion in the travel time dimension increases with the respondents' age and decreases with their level of education. Further, our results suggest that people tend to be more loss averse when the reference is well established: the respondents exhibit more loss aversion in an experiment, where the reference point is assumed to be a recently made trip, than in an experiment where the reference is assumed to be a similar (potentially hypothetical) trip with another transport mode. This effect is particularly strong if the respondent rarely makes such a trip.

In Chapter 5, *Cumulative prospect theory applied to stated preference data with travel time variability*, I analyse preferences for travel time variability (TTV). Generally, preferences for TTV are measured using SP data, where an often applied format is to present respondents with travel time distributions given by a list of five or more equally likely outcomes (see, e.g. de Jong et al., 2007; Fosgerau et al., 2008). A com-

[4]Vol. 49(4), 2011; doi: 10.1007/s10640-010-9455-5.

mon feature for most studies is that they assume that travellers' choices maximise their expected utility. However, evidence from the economic literature about risk attitudes and choice under risk suggests that subjects' behaviour in laboratory experiments exhibits "anomalies" as probability weighting and reference-dependence (Hey and Orme, 1994; Harless and Camerer, 1994; Loomes et al., 2002; Stott, 2006; Harrison and Rutström, 2009), and it seems likely that this may also apply to behaviour in SP experiments with risky travel times.

I therefore analyse preferences for TTV using a model based on cumulative prospect theory, which accommodates both rank-dependent probability weighting and reference-dependence. I apply the model to a standard TTV SP experiment, with choices between travel alternatives that are characterized by a monetary cost and a discrete travel time distribution with five mass points.

The results show that the respondents' behaviour is consistent with the behavioural premises from cumulative prospect theory, and indicate significant probability weighting. The results vary, depending on the assumed functional form of the weighting function, but indicate that respondents tend to overweight the likelihood of the extreme outcomes: the largest gain, the smallest gain, the smallest loss, and the largest loss.

This result has consequences for the way SP experiments about TTV are designed: When respondents weight travel time outcomes differently from what the experimenter intends, the results from such SP experiments cannot be applied in forecasts and welfare analyses, since we cannot be sure how the probability weighting in the SP experiment is related to travellers' behaviour in real life.

References

Avineri, E., Bovy, P., 2008. Parameter identification of prospect theory model for travel choice analysis. Transportation Research Record 2082, 141–147. [3]

Bateman, I., Munro, A., Rhodes, B., Starmer, C., Sugden, R., 1997. A test of the theory of reference-dependent preferences. Quarterly Journal of Economics 112, 479–505. [6]

Burge, P., Rohr, C., Vuk, G., Bates, J., 2004. Review of international experience in VOT study design. European Transport Conference 2004. [5]

De Borger, B., Fosgerau, M., 2008. The trade-off between money and travel time: A test of the theory of reference-dependent preferences. Journal of Urban Economics 64, 101–115. [5]

de Jong, G., Tseng, Y., Kouwenhoven, M., Verhoef, E., Bates, J., 2007. The value of travel time and travel time reliability: Survey design. Final report. Report to The Netherlands Ministry of Transport, Public Works and Water Management. [5, 6]

de Lapparent, M., Ben-Akiva, M., 2011. Risk aversion in travel mode choice model with rank dependent utility. Forthcoming in Mathematical Population Studies. [4]

Fosgerau, M., Hjorth, K., Brems, C., Fukuda, D., 2008. Travel time variability: Definition and valuation. DTU Transport, Report to The Danish Ministry of Transport. [6]

Fosgerau, M., Hjorth, K., Lyk-Jensen, S. V., 2007. The Danish Value of Time Study: Final report. Report for the Danish Ministry of Transport, Danish Transport Research Institute. [3, 4, 5]

Gunn, H., 2001. Spatial and temporal transferability of relationships between travel demand, trip cost and travel time. Transportation Research, Part E 37, 163–189. [5]

Harless, D., Camerer, C., 1994. The predictive utility of generalized expected utility theories. Econometrica 62, 1251–1289. [7]

Harrison, G., Rutström, E., 2009. Expected utility theory and prospect theory: one wedding and a decent funeral. Experimental Economics 12, 133–158. [7]

Hensher, D. A., Li, Z., 2011. Valuing travel time variability within a rank-dependent utility framework and an investigation of unobserved taste heterogeneity, forthcoming in Journal of Transport Economics and Policy. [4]

Hey, J., Orme, C., 1994. Investigating generalizations of expected utility theory using experimental data. Econometrica 62, 1291–1326. [7]

Hultkrantz, L., Mortazavi, R., 2001. Anomalies in the value of travel-time changes. Journal of Transport Economics and Policy 35, 285–300. [5]

Kahneman, D., Tversky, A., 1979. Prospect theory: An analysis of decision under risk. Econometrica 47, 263–291. [3]

Loomes, G., Moffatt, P., Sugden, R., 2002. A microeconometric test of alternative stochastic theories of risky choice. Journal of Risk and Uncertainty 24, 103–130. [7]

Mackie, P., Fowkes, A., Wardman, M., Whelan, G., Nellthorp, J., Bates, J., 2003. Values of travel time savings in the UK – Report to Department for Transport. Institute for Transport Studies, University of Leeds, in association with John Bates Services. [4, 5]

Mackie, P., Jara-Díaz, S., Fowkes, A., 2001. The value of travel time savings in evaluation. Transportation Research, Part E 37, 91–106. [5]

Michea, A., Polak, J., 2006. Modelling risky choice behaviour: Evaluating alternatives to expected utility theory. 11th International Conference on Travel Behaviour Research, Kyoto, Japan. [4]

Quiggin, J., 1982. A theory of anticipated utility. Journal of Economic Behavior and Organization 3, 225–243. [3]

Ramjerdi, F., Flügel, S., Samstad, H., Killi, M., 2010. Den norske verdsettingsstudien, Tid. Report for the Norwegian Ministry of Transport, Institute of Transport Economics, Oslo, Report no. 1053B/2010. [4, 5]

Samstad, H., Ramjerdi, F., Veisten, K., Navrud, S., Magnussen, K., Flügel, S., Killi, M., Halse, A. H., Elvik, R., Martin, O. S., 2010. Den norske verdsettingsstudien, Sammendragsrapport. Report for the Norwegian Ministry of Transport, Institute of Transport Economics, Oslo, Report no. 1053/2010. [3]

Stott, H., 2006. Cumulative prospect theory's functional menagerie. Journal of Risk and Uncertainty 32, 101–130. [7]

Tversky, A., Kahneman, D., 1991. Loss aversion in riskless choice: A reference-dependent model. The Quarterly Journal of Economics 106 (4), 1039–1061. [3]

Tversky, A., Kahneman, D., 1992. Advances in prospect theory: Cumulative representation of uncertainty. Journal of Risk and Uncertainty 5, 297–323. [3]

Van de Kaa, E., 2005. Heuristic judgment, prospect theory and stated preference surveys aimed to elicit the value of travel time. European Transport Conference 2005. [3]

Van de Kaa, E., 2008. Extended prospect theory – findings on choice behaviour from economics and the behavioural sciences and their relevance for travel behaviour. Doctoral thesis, TU Delft. [3]

Chapter 2

Between-mode-differences in the value of travel time: Self-selection or strategic behaviour?

Between-mode-differences in the value of travel time: Self-selection or strategic behaviour?

Mogens Fosgerau, Katrine Hjorth, and Stéphanie V. Lyk-Jensen
Published in *Transportation Research Part D: Transport and Environment*.[1]
Printed with kind permission of Elsevier.

Abstract

Using stated preference survey data, we measure the value of travel time for several transport modes. We find, like many before us, that the value of travel time varies across modes in the opposite direction of what would be the consequence of differences in comfort. We examine three candidate causes for the observed differences: Comfort effects, self-selection and strategic behaviour of respondents. Using experiments with both the current and an alternative mode we find that the differences in the value of travel time are consistent with self-selection and comfort effects. Moreover, respondents having bus as the current or the alternative mode seem not to value comfort differently across modes. Strategic behaviour seems to play no role.

2.1 Introduction

The value of travel time (VTT) is arguably the single most important concept in transport economics. It largely drives the result of most cost-benefit analyses of transport projects and it is a fundamental driver of the results of traffic forecasts. Numerous studies in Europe, the US, South-America and Australia have been devoted to the estimation of values of travel time: See, e.g., Wartburg and Waters II (2005) and Wardman (1998, 2004) for reviews. While early work mainly focused on car travel time, more recent studies also involve travel time in public transport (PT). It is a common finding that the VTT for car is larger than the VTT for PT. Such differences have strong implications for the appraisal of transport projects where it could lead to a preference for road projects and against the more environmentally friendly PT modes. As a consequence, some countries choose to ignore these empirical differences and use a single appraisal value of travel time for all transport modes to avoid what is perceived as an unfair comparison between road projects and PT projects.

The purpose of this paper is to investigate the sources of variation across modes in the measured VTT. As concluded by Wardman (2004), most of the VTT studies reviewed at that time fail to disentangle the user type effects, i.e. the variation in the value of a travel time saving in a given transport mode between the users of different modes; and mode effects, i.e. the variation in VTT across transport modes for a given individual.

[1] Vol. 15(7), 2010; doi: 10.1016/j.trd.2010.04.005. This version is a slightly revised version of the journal version: Notation has been adapted to the style of the thesis, a few clarifying remarks have been added, and a misprint in the data description has been corrected.

The present paper proposes an econometric framework controlling for respondent and trip characteristics that enables us to disentangle these effects. We examine three candidate causes for the observed differences in VTT: Comfort effects, self-selection and strategic behaviour of respondents.[2] These issues are not specific to VTT studies but are general to valuation studies, including those of environmental effects. For this reason, the results in the present paper may be of interest from an environmental perspective.

Because travelling by bus is less comfortable than travelling by car we would expect the VTT to be higher for bus than for car. Our expectation is more ambiguous for the VTT in train relative to car. However, our expectations regarding comfort effects seem to be at odds with the findings from empirical valuation studies. In a UK valuation study, Mackie et al. (2003) find similar VTT values for train and car, and somewhat lower values for bus, and conclude that aggregating across individuals to the level of user types causes a reverse valuation pattern compared to that predicted by comfort effects.[3]

Mackie et al. (2003) note that it is the characteristics of bus travellers, and not the mode per se, which causes the average VTT on bus to be low. They suggest that the VTT pattern is due partly to observable differences between the users of different modes, such as income differences and differences in journey lengths, and partly due to self-selection – individuals migrating to modes whose characteristics suit their own: We expect that individuals having high VTT, ceteris paribus, are more likely to choose the fast modes, such as car and train, while those with low VTT tend to choose the bus.

Another potential explanation for the observed differences between modes is strategic behaviour (or policy bias). Respondents in a stated preference experiment might think outside the context of the experiment and consider their ability to influence political decisions. It is possible that car drivers and PT users differ in their perception of the political consequences of the survey: Car drivers may feel that it is a free lunch to express a wish to pay for increased speed, because there is no established mechanism whereby they could actually pay for reduced travel times. Conversely, PT passengers pay fares set by political decisions while travel times may be deemed difficult to change as they are determined by traffic conditions and not politically. Passengers may hope that expressing a low willingness-to-pay may influence the setting of fares. In both cases, choices cannot be seen as an expression of preferences. This strategic behaviour explanation has very serious consequences: If respondents do not reveal their true preferences, the results from the survey are likely to be misleading.

Our empirical analysis uses a stated preference data set collected for a Danish VTT study (Fosgerau et al., 2007a). To investigate whether self-selection or strategic behaviour drives the empirical differences in VTT across modes, we must identify mode effects separately from user type effects. The observation of people's VTT in their chosen transport mode alone is not sufficient to separate these effects. However, the

[2]We use the term comfort effects to encompass all effects of differences in mode characteristics, such as level of crowding, seat availability, noise, and reliability.

[3]Similar results are found in Norway (Ramjerdi et al., 1997), Switzerland (Axhausen et al., 2004), and Denmark (Fosgerau et al., 2007a), as well as in a meta-analysis of European VTT studies (Shires and de Jong, 2006). In Fosgerau et al. (2007a), the VTT differences remain even after controlling for income effects.

experimental design of the Danish VTT study provides us with an instrument to control for the self-selection into transport modes: The stated choice survey includes both an experiment measuring the VTT in the current mode of the respondents, but also a similar experiment for an alternative mode. Consequently, we observe the same individual's VTT in different modes, and can thereby disentangle mode effects from user type effects.

We use a mixed logit framework to model respondents' responses as a function of their VTT. We assume a distribution of VTT in the population with the individual VTT being partly explained by observed variables, partly by unobserved taste variation. The observed variables include the current and alternative modes of the respondent, in combination with the mode in which the VTT is measured. In this way, we estimate separate VTT distributions for each 'user type' (defined by current and alternative mode), and for each mode in which this user type is observed. We can then detect mode effects by comparing distributions within the same user group, while user type effects are measured by comparing across user groups.

2.2 Decomposition of the VTT

Becker (1965) formalised the concept of a value of time within a microeconomic framework. He argued that the consumer's utility depends not only on the direct consumption of goods, but also indirectly on the allocation of time to good consumption. Becker's model was further developed by Oort (1969) and DeSerpa (1971) [4]: In DeSerpa's model, the utility function depends directly on the pleasantness of the time allocated to different activities, and the traveller maximises utility subject to budget constraints with respect to time and money and technical constraints on the minimum amount of time necessary to allocate to each activity. In this setup, DeSerpa derives the marginal value of saving travel time (VTT) as the marginal value of leisure time minus the marginal value of the utility of travelling.[5] The latter is often referred to as the value of travel time as a commodity (DeSerpa, 1971) or the value of time assigned to travel (Jara-Díaz and Guevara, 2003).

How factors such as comfort and socio-economic variables affect VTT is often left to empirical analysis.[6] The value of leisure depends on characteristics of the individuals who travel (user type effects), but not on the transport mode considered, while the disutility of travelling may depend on both. As a consequence user type effects work both through the value of leisure and the disutility connected with travel time, whereas mode effects only work through the latter component.

Econometric identification of mode effects and user type effects is made difficult by a potential selection problem, since many surveys measure an individual's VTT in

[4] For a review of the literature on time allocation and valuation, see Jara-Díaz (2007).

[5] Jara-Díaz (2003) extends this framework with a model that allows a more general specification of the technical relations between time assignment and goods consumption. He shows that the VTT contains not just the two components from DeSerpa's model, but also a component representing the value of a change in the consumption pattern due to a travel time saving.

[6] An exception is Jiang and Morikawa (2004) who use the theoretical framework to derive the variation in VTT with respect to travel time, wage, and work time.

his chosen mode only. Self-selection is generally present as soon as inclusion into the sample is a result of individual decisions in the population of interest, and it is a major topic in the econometrics literature because it leads to inconsistent estimates.

Correcting for self-selection requires the use of instruments that can be difficult to find. Eklöf and Karlsson (1999) propose a methodology for correcting sample selection bias in discrete choice contingent valuation studies, and Mabit and Fosgerau (2006) apply Heckman (1979)'s correction methodology to the case of the VTT. We exploit that the experimental design of the Danish VTT study (Fosgerau et al., 2007a) directly provides us with an "instrument": The survey not only includes an experiment measuring the VTT in the chosen mode, but also a similar experiment for an alternative mode, making it possible to observe the same individual's VTT in different modes, and to disentangle mode effects from user type effects.

VTT studies in the Netherlands, the UK, Norway, and Sweden have also tried to identify user type effects and mode effects. In the Dutch study of car and train users' VTT, both user types have higher VTT in train than in car (which reflects the comfort differences), and car users generally have lower VTT than train users (Wardman, 2004). The user type effect is relatively small compared to the mode effect but this is most likely because the two user types are quite similar – in another Dutch study which also includes bus and tram users, the user type effects are more prominent (Wardman, 2004). The UK study finds that car users have higher VTT in bus compared to car, and lower VTT in train compared to car (Mackie et al., 2003). This finding can also be interpreted as a comfort effect. The evidence from Norway and Sweden is very limited.

Jara-Díaz and Guevara (2003) and Munizaga et al. (2006) do not distinguish between user type effects and mode effects, but instead estimate the marginal value of leisure and the VTT separately in two distinct estimations (for the same sample). The marginal value of leisure is estimated from time assignment data, while the VTT is estimated from mode choice data. From these two estimations, the marginal value of time assigned to travelling can be inferred. They find that the marginal value of leisure is quite small compared to the marginal value of time assigned to travelling, implying that mode effects have potentially large impact. However, since they assume a constant VTT across transport modes, their results cannot be used to distinguish user type effects from mode effects.

2.2.1 Self-selection or strategic behaviour

Previous studies found that car drivers have considerably higher VTT than PT users. Self-selection is a potential cause, reflecting that individuals with high VTT may more often prefer car or train to bus, and that this self-selection is not appropriately controlled for. In this case, the measured VTT for car drivers and train passengers (bus users) will be upwards (downwards) biased as measures of VTTs in the population. The variation caused by such biases does not, however, reflect comfort effects, and should not be interpreted to say that any given individual would pay more to save travel time in car than in bus.

Another potential explanation of the observed VTT pattern could be respondents' strategic behaviour. As we previously argued, car drivers may have an incentive to overstate their VTT in the stated preference experiment, and PT users may have an incentive to understate their VTT. In this case, the measured VTT for car drivers (PT users) will be upwards (downwards) biased.

To investigate whether self-selection or strategic behaviour drives the observed VTT differences, we estimate the VTT for different user types (car drivers, bus passengers, and train passengers) in their chosen transport mode and in an alternative transport mode (car, bus, or train). These estimations allow us to separate mode effects from user type effects, as mode effects can be identified by comparing the valuations of a given user type in different transport modes. Once mode effects and user type effects are separately identified, we can distinguish between the two hypotheses: self-selection or strategic behaviour.

Under the self-selection hypothesis we would expect respondents to carry their unobserved value of leisure with them to the alternative mode so that only the disutility of travelling may change due to comfort effects. Thus car drivers and train users would have higher VTT in bus than bus users, and bus users would have lower VTT in car (train) than car drivers (train users). Conversely, strategic responses will result in lower VTT of car drivers as they go to bus (train) and the opposite for bus and train passengers.

2.3 Data

2.3.1 Sampling and interviews

The data stem from the Danish VTT survey (Fosgerau et al., 2007a). They encompass private trips for commuting and other purposes (not business trips) with car and public transport modes.[7] The survey used an on-line questionnaire containing a series of stated preference experiments, where respondents trade travel time for money.

Respondents were sampled from Gallup's Danish web and phone panels or contacted at educational institutions.[8] Respondents from the web panel were asked to complete the questionnaire on the Internet, while the remaining respondents were face-to-face interviewed using the same questionnaire on a laptop.

To fulfil sampling quotas on transport mode, trip length and trip purpose, each respondent was asked to report the mode, length, and purpose of all trips made during the last eight days, and one of these trips was selected randomly based on the quotas. We label this trip *the reference trip*. The mode of transport on the reference trip is denoted *the current mode*. After answering a series of background questions regarding the reference trip, the respondent participated in the first stated preference experiment (SP1), which measured his VTT in his current mode.

Afterwards the respondents were asked whether an alternative transport mode would be available for the reference trip if the current mode was unavailable. In this case, we define *the alternative reference trip* as the reference trip as it would have been, if made with the alternative mode. Respondents who had an alternative mode (and had used

[7] See Burge and Rohr (2004), for further details on the SP design.

[8] The web panel is representative of the Danish population aged 15-59 with Internet access. The phone panel is representative of the entire Danish population.

Table 2.1: Distribution of respondents on modes

Current mode	Alternative mode			
	Car	Bus	Train	None
Car		225	201	1575
Bus	122		25	952
Train	110	29		706

this mode for some type of trip within the last year) then participated in another stated preference experiment (SP2) that measured their VTT in the alternative mode.

After participating in the experiments, respondents answered background questions regarding their socio-economic status.

2.3.2 The stated preference experiments

In both SP1 and SP2, the VTT was measured indirectly in terms of trade-offs between travel time and travel cost. SP1 measured the VTT in the respondent's current mode, while SP2 measured VTT in the alternative mode.

Each experiment comprised eight binary route choices, where the proposed route alternatives varied by travel time and travel cost, such that one alternative was faster and more expensive than the other. In SP1, respondents were furthermore presented with a dominated choice, where one alternative was both faster and cheaper than the other. This choice served as a check question and is not included in our analysis.

The attribute levels were designed by pivoting around reference values of the travel time and cost. In SP1, these reference values are the travel time and cost of the reference trip. In SP2, the reference values are the travel time and cost of the alternative reference trip, as perceived by the respondent. The travel time corresponds to in-vehicle time only. For multiple-mode PT trips, it is the in-vehicle time for the mode used on the main part of the trip (in terms of duration).

The time and cost attributes were varied around the reference to make four types of choices, defined by quadrants in the (time, cost)-plane. In the willingness-to-pay (WTP) quadrant, the choice is between the reference and a faster and more expensive trip, while in the willingness-to-accept (WTA) quadrant the choice is between the reference and a slower and cheaper trip. In the equivalent gain (EG) quadrant, the choice is between a gain in time and a gain in money, while in the equivalent loss (EL) quadrant the choice is between a loss in time or in money. The eight choices in each experiment were distributed with two in each of the four choice quadrants.

If the reference travel time was less than or equal to 10 minutes, the time attribute varied around the reference time plus two minutes (such that it could still vary both up and down). Hence, choice quadrants were defined relative to this transformed reference.

Table 2.2: Descriptive statistics (of observations in SP1 and SP2)

	Min	Mean	Max
y (choice variable)	0.000	0.388	1.000
$\log v$	-2.996	-0.554	1.209
$\min(\Delta t - 15, 0)$	-12.000	-7.672	0.000
Commuter dummy	0.000	0.221	1.000
Log (reference travel cost)	0.000	3.243	6.745
Log (reference travel time)	1.609	3.464	6.131
Log (personal income), demeaned	-1.334	-0.186	1.060
Low income dummy	0.000	0.154	1.000
Missing income dummy	0.000	0.071	1.000
Greater Copenhagen Area dummy	0.000	0.245	1.000
Age 31-65 dummy	0.000	0.626	1.000
Age 66+ dummy	0.000	0.114	1.000
Female dummy	0.000	0.510	1.000

Note: $\Delta t > 0$ is the travel time difference between the two alternatives (in min). v is the ratio between the cost difference and the travel time difference (in DKK/min).

Table 2.3: Familiarity with alternative mode

Current mode	Alternative mode	Share of resp. using alt. mode more often than current mode on trips with same origin /destination as reference trip	Share of resp. never using alt. mode on trips with same origin/destination as reference trip
Car	Bus	1%	36%
Car	Train	0%	46%
Bus	Car	30%	7%
Bus	Train	12%	20%
Train	Car	15%	13%
Train	Bus	3%	24%
All	Car/Bus/Train	8%	29%

2.3.3 Descriptive data

The background variables available from the interviews are socio-economic characteristics (e.g. age, net income, gender, household status etc.) together with details of the reference trip and the alternative reference trip.[9]

We exclude respondents who chose the dominated alternative (that being slower and more expensive) in the check question (11%). Due to rounding, there were a number of other occasions where respondents were presented with dominated choice situations, e.g., with the same cost in both situations. These choice situations were also excluded as they contain no information about the value of time. Further, we exclude respondents who gave unrealistic answers concerning travel distance, travel time, travel cost, calculated speed, share of travel time due to congestion, and travel group size (9%). Finally, we exclude respondents whose reference trip is paid by the employer (4%). In such cases the respondents' choices are most likely not indicative of their own marginal utility of money. The remaining sample encompasses 3945 individuals with a total of 36,093 choices.

Table 2.1 summarises the sample distribution on current and alternative mode. We only consider respondents whose current mode is car (driver), bus, or train, and whose alternative mode is car (driver), bus, train, or none. As shown in Table 2.1, this makes nine user types defined by current/alternative mode. Even though many respondents indicate no alternative mode, there are sufficient observations of respondents who do indicate an alternative mode. Descriptive statistics of the sample are shown in Tables 2.2 - 2.3. In general, the current mode is the mode used most often on the trip, and it seems that current PT users with car as alternative have a reasonable knowledge about their alternative reference trip, while current car users do not know their alternative reference very well (Table 2.3). Recall that a condition for participation in the alternative mode experiment was that respondents had used the alternative mode for some type of trip within the last 12 months. What Table 2.3 indicates is that some have not used the alternative mode on trips with the same origin and destination as the reference trip.

It is interesting to compare the travel time and cost of the reference trip to those of the alternative reference trip. Before we do so, however, we stress that such a comparison has its limitations, for the following two reasons:

- For a given transport mode (car, bus or train), the reference travel time is the travel time spent in-vehicle in this mode. Since PT trips more often include access and egress travel time or multiple transport modes, it is likely that the reference travel time for a PT trip makes up a smaller part of the total travel time than does the reference travel time for a car trip. This difference may explain why some respondents have longer in-vehicle travel time in car than in bus.
- For PT trips, the reference cost is the cost of the entire trip. For car trips, it is the direct driving costs (including bridge tolls and parking costs, but excluding fixed car costs).

[9] Subjects stated their gross annual income, grouped into intervals of 100,000 DKK up to 1 million DKK (1 Euro $\approx$ 7.5 DKK). We have computed net annual income by applying national tax rates to interval midpoints.

Figures 2.1 - 2.3 in the Appendix plot the difference in travel times between the reference trip and the alternative reference trip against the difference in cost for different combinations of available modes. The Figures reveal some characteristics of the different user types. First, current car and train users choose the faster mode to a larger extent than current bus users, while bus users have a larger tendency to choose the cheaper mode. These findings support the hypothesis of self-selection. Second, it seems that a majority of the current car users have lower cost and lower travel time in the car than in PT. This finding is consistent with rational behaviour but should be interpreted with care, because the car costs are likely to include only part of the marginal monetary cost. In addition, the high share of current car users who never use the alternative mode on trips like the reference trip (36-46%, Table 2.3), could indicate that car users may have a biased perception of the travel time and cost of the alternative reference trip.

2.4 Model

Let $\Delta t > 0$ and $\Delta c > 0$ denote the difference in travel time and cost, respectively, between the two alternatives in a given choice. Fosgerau (2007) uses non-parametric techniques to test different parametric discrete choice model specifications, and finds that a model with the following features describes the data well:

(a) An individual chooses the faster alternative when the logarithm of his VTT exceeds the logarithm of the boundary value of time presented in the choice, $v := \frac{\Delta c}{\Delta t}$, plus an additive random error.

(b) The log VTT is defined as a linear index of covariates plus an additive independent residual.

This result is the starting point of the modelling approach developed in the Danish VTT study (Fosgerau et al., 2007b) and the modelling approach we adopt here.

2.4.1 VTT distribution

Following (b), we assume that the VTT can be parameterised as:

$$\log VTT_{is} = \beta' x_{is} + \delta' z_{is} + u_i, \tag{2.1}$$

where i indexes the individual, s the choice situation, x is a vector of background and trip characteristics, z is a vector of mode characteristics, and u is an individual-specific $N(0, \sigma^2)$ random variable independent of x and z.

This implies i) that the VTT conditional on x and z varies randomly in the population to allow for unobserved heterogeneity, following a lognormal distribution, and ii) that the unobserved heterogeneity affects the VTT in the current and the alternative mode in same way in the two experiments. The assumption that VTT is lognormal is made for the sake of simplicity, even though Fosgerau et al. (2007b) conclude that the distribution of (current) car drivers' VTT in car is more right-skewed than the lognormal, while the distribution of (current) bus users' VTT in bus is less right-skewed than the lognormal. The assumption of a lognormal distribution of the conditional VTT is not so restrictive since we are interested in the location of the distribution of conditional VTT rather than in estimating its mean.

The covariate vector x contains a constant, socio-economic variables (personal income, a geographical variable, age and gender), trip characteristics (reference travel time, reference travel cost, and a dummy for commuting trips[10]), and quadrant dummies to account for differences in the VTT across quadrants, which are often observed in willingness-to-pay studies (Horowitz and McConnell, 2002).[11] Further, we assume that log VTT increases linearly with the absolute value of the time difference between the two alternatives (Δt) up to 15 minutes where it becomes constant, and therefore include the term $\min(\Delta t - 15, 0)$ in x (cf. Fosgerau et al., 2007b).

The vector z contains a set of mode dummies, one for each combination of current mode, alternative mode, and experiment. The dummies are denoted z^{CN1}, z^{CB1}, z^{CB2} ... with corresponding parameters δ^{CN1}, δ^{CB1}, δ^{CB2} .... The first letter in the superscript denotes the current mode (C=car, B=bus, or T=train), the second the alternative mode (C, B, T, or N=none), and the third the experiment (SP1 or SP2). For identification, we normalize the parameter for bus users with no alternative mode to zero: $\delta^{BN1} = 0$.

With this notation, the VTT in a choice r from the car experiment (SP1) for an individual i with car as current mode and train as alternative mode is:

$$VTT_{ir}^{CT1} = \exp(\beta' x_{ir} + \delta^{CT1} + u_i), \tag{2.2}$$

while the VTT in a choice s from the train experiment (SP2) is:

$$VTT_{is}^{CT2} = \exp(\beta' x_{is} + \delta^{CT2} + u_i). \tag{2.3}$$

In our model, x captures all observed user type effects, while z captures mode effects and average unobserved user type effects. What we are interested in is the distribution of VTT conditional on x, which in this simple model only depends on the mode dummies and is otherwise the same for all individuals, because of the assumption of no interaction between x and z.

Conditional on x we estimate separate VTT distributions for each user type and each experiment. These distributions have the same scale parameter (σ), but different location parameters (the δ's). Since the mean value of a lognormal variable e^{ω} with $\omega \sim N(a, b^2)$ is $E(e^{\omega}) = \exp(a + b^2/2)$, the ratios of the means of the conditional VTT distributions depend only on δ. For example the mean VTT in car for the user group with car as current mode and train as alternative mode relative to the mean VTT in car for the user group with train as current mode and car as alternative mode is:

[10] Only the distinction between commuting and other travel purposes was significant.

[11] We expect the interpretation of quadrants to be somewhat different for respondents with transformed reference, as we expect respondents to view alternatives in comparison with their real reference trip. Hence, what is a WTP (or EG) choice relative to the transformed reference, is something in between a WTP and EL (EG and WTA) choice relative to the reference. This is approximately incorporated into the model by imposing linear constraints on the parameters (details are available on request).

$$(2.4) \qquad \frac{E(VTT^{CT1}|x)}{E(VTT^{TC2}|x)} = \exp(\delta^{CT1} - \delta^{TC2}).$$

By estimating relations such as eq. (2.4) we can compare VTT across user types and modes and identify signs of self-selection or strategic behaviour.

2.4.2 Choice model

Define the choice variable y_{is}, which takes the value one when respondent i chooses the faster and expensive alternative in choice s, and zero otherwise. Following (a) and (b), we assume that:

$$(2.5) \qquad y_{is} = 1, \quad \text{iff} \quad \log VTT_{is} + \frac{\varepsilon_{is}}{\mu} > \log v_{is},$$

where

$$(2.6) \qquad v_{is} = \frac{\Delta c_{is}}{\Delta t_{is}},$$

and the error terms ε_{is} are iid logistic random variables with mean zero and variance $\pi^2/3$. The parameter μ is the error scale and is assumed to be the same for all user types and transport modes.

The distributional assumptions on the ε_{is}'s imply that the probability that individual i makes his observed choice sequence $(\tilde{y}_{i1} \dots \tilde{y}_{iS})$, conditional on observables and unobserved heterogeneity, is given by:

$$(2.7) \qquad \begin{aligned} & P\left((y_{i1} \dots y_{iS}) = (\tilde{y}_{i1} \dots \tilde{y}_{iS}) | \{x_{is}, z_{is}, v_{is}\}_{s=1}^{S}, u_i\right) \\ &= \prod_{s=1}^{S} P(y_{is} = 1 | x_{is}, z_{is}, v_{is}, u_i)^{\tilde{y}_{is}} P(y_{is} = 0 | x_{is}, z_{is}, v_{is}, u_i)^{1-\tilde{y}_{is}} \\ &= \prod_{s=1}^{S} \left(\frac{1}{1+\exp(-\mu(\log VTT_{is} - \log v_{is}))} \right)^{\tilde{y}_{is}} \left(\frac{\exp(-\mu(\log VTT_{is} - \log v_{is}))}{1+\exp(-\mu(\log VTT_{is} - \log v_{is}))} \right)^{1-\tilde{y}_{is}} \end{aligned}$$

Given $u_i \sim N(0, \sigma^2)$, the likelihood function becomes:

$$(2.8) \qquad L = \prod_i \int P\left((y_{i1} \dots y_{iS}) = (\tilde{y}_{i1} \dots \tilde{y}_{iS}) \,|\, \{x_{is}, z_{is}, v_{is}\}_{s=1}^{S}, u\right) f(u)\, du$$

where f is the density function of $N(0, \sigma^2)$. This is a panel formulation assuming that u_i is fixed over observations from the same respondent.

Table 2.4: Relative mean VTT, after controlling for covariates (bus-none normalized to one)

Current mode	Alternative mode	Experiment mode		
		Car	Bus	Train
Car	None	1.21		
Car	Bus	1.36	1.25	
Car	Train	1.37		1.56
Bus	None		1.00	
Bus	Car	1.06	0.90	
Bus	Train		0.79	0.71
Train	None			1.36
Train	Car	0.94		1.45
Train	Bus		0.97	0.73

2.5 Results

Estimation is carried out using the software Biogeme (Bierlaire, 2003, 2005). We use 300 Halton draws to simulate each likelihood contribution and note that this is sufficient to achieve stable results (cf. Train, 2003). Table 2.4 gives the resulting relative VTT values, while the parameter estimates can be seen in Table 2.5 in the Appendix. Table 2.6 (also in the Appendix) gives a series of likelihood ratio tests of relevant restrictions on the parameters.

While our purpose of the paper is not to discuss the estimated β's in detail, we can underline that most of them are significant and have the expected signs, e.g. the VTT increases with income and with the size of the time saving, and it varies between the choice quadrants, such that WTP choices have significantly lower VTT than WTA choices (this is consistent with loss aversion, cf. De Borger and Fosgerau, 2008).

Table 2.4 shows the relative mean VTT values, once all observed user type effects have been controlled for. These values are computed as in eq. (2.4), with the mean VTT for bus users with no alternative mode ($E(VTT^{BN1}|x)$) as the common denominator.

The left part of the table lists the nine user types by current and alternative mode. The right hand side shows the relative mean VTT values. The experiment mode indicates the mode in which VTT is measured. For example, the top row reads: The mean VTT in car for car users with no alternative is 1.21 times the mean VTT in bus for bus users with no alternative.

By construction of the table, user type effects (e.g., self-selection) are identified by comparing different rows within the same column. Mode effects (as comfort effects or strategic behaviour) are identified by comparing columns within the same row.

We begin by looking at user type effects. Recall that in the case of self-selection, we expect car drivers and train users to have higher VTT in bus than bus users. Bus users would have lower VTT in car (respectively train) than car drivers (respectively train users).

Our results show that even though train users' VTT in train is higher than car drivers' VTT in car, car drivers in general have the highest VTT values: A column-wise comparison of the current car drivers to the other user types shows that current car drivers have the highest VTT in car, in bus, and in train. Current bus users in general have the lowest VTT values.

Looking into the results in more detail, consider first the respondents with car and bus as experiment modes. Here the current car drivers have higher VTT in car than current bus passengers: 1.36 versus 1.06. The difference is not significant at the 5% level, however: A likelihood ratio test cannot reject the hypothesis that the two user types have a common VTT in car (Table 2.6). The current car drivers also have the highest VTT in bus, and this difference is significant. Both results indicate self-selection, and show a tendency for respondents with high VTT (after controlling for observables) to choose car rather than bus.

Subsequently, we look at the respondents with car and train as experiment modes. Once more, the results point in the direction of self-selection: Current car drivers have higher VTT than current train passengers, both in car and in train, though only the first of these differences is significant (Table 2.6).

For respondents with bus and train as experiment modes, the current train users have the higher VTT in both bus and train. However, these differences are very insignificant, probably as a result of the small sample sizes.

The overall conclusion regarding user type effects is that self-selection seems a credible explanation, even though some effects are not significant. This evidence is consistent with the revealed preference evidence in Figures 2.1 - 2.3.

We now turn to look at mode effects. In case of comfort effects, we expect any user group to have lower VTT in car than in public transport, and a lower VTT in train than bus. Mode effects in the opposite direction would be interpreted as signs of strategic behaviour.

First, we note that the relative means for current bus passengers are all close to 1.00. In fact, they are not significantly different from 1.00 – a joint likelihood ratio test that all mean values for current bus passengers are identical cannot be rejected (Table 2.6). Hence there is no significant mode effect among current bus passengers – saving time in one mode is worth the same as saving time in another mode.

Interestingly, this finding also holds for respondents with bus as alternative. For train users with bus as alternative the VTT in train does not differ significantly from the one in bus, and for car users with bus as alternative the VTT in car is not significantly different from that in bus (Table 2.6). Hence it looks like respondents who take the bus or would take the bus as alternative mode do not care which mode they are in – in the sense that saving travel time is worth the same in any mode.

Finally, we look at respondents with car and train as experiment modes. Both current car drivers and current train passengers have higher VTT in train than in car, and both effects are significant. These mode effects are consistent with the differences in comfort, and give no sign of strategic behaviour.

2.6 Conclusions

Our results indicate that user type effects in the form of self-selection are a main driver behind the variation in VTT across modes. Once user type effects are controlled for, we are able to observe the underlying mode effects. For the respondent groups having the lowest VTT (current bus users and respondents who would use the bus as alternative) no significant mode effects can be found. It thus seems that only respondents with high VTT are affected by the experiment mode. Among those, the VTT is significantly lower in car than in train, which is consistent with the differences in comfort. We cannot find evidence of strategic behaviour.

The discrete choice model applied in the paper is well suitable to disentangle user type effects and mode effects because of its direct parameterisation of the VTT. It does, however, have two restrictive assumptions, namely that the VTT distributions have the same scale parameter (σ), and that they are all lognormal. We have tried relaxing the former assumption, and though it complicates the analysis, the overall conclusions remain the same.

Regarding the distributional assumption, Fosgerau et al. (2007b) find that the VTT distributions for SP1 data for car and bus differ significantly from the lognormal distribution: The true car distribution is more right-skewed than the lognormal, and the true bus distribution is less right-skewed. However, Hjorth (2007) suggests that the overall VTT pattern does not change much when allowing for more flexible VTT distributions.

There are some potential sources of bias that we are not able to control for. The hypothetical nature of the experiment can cause bias if the respondents' stated behaviour differs from their actual behaviour. This bias is especially relevant when measuring VTT in the alternative mode: If respondents are not familiar with their alternative reference trip, they might not even know their actual behaviour in the alternative experiment. This lack of familiarity with the alternative mode could pose a problem here, since most current car users do not know their alternative reference trip very well.

Another issue is that we rely on a within-sample comparison rather than a between-sample comparison. We observe the same sample in different modes. The potential problem with this within-sample comparison is that respondents in the second experiment may feel they need to be consistent with the answers they gave in the first experiment, e.g. by stating a high VTT in the second experiment because they stated a high VTT in the first. There could also be some sort of anchoring bias, pulling the VTT in the second experiment towards the VTT in the first. If such effects are present, it would cause the mode effects to be underestimated. This is another possible explanation of the many respondents who do not exhibit mode effects. However, the advantage of a within-sample comparison is that we can control for the effect of unobserved heterogeneity that is likely to affect VTT in the same direction in both experiments.

References

Axhausen, K., König, A., Abay, G., Bates, J., Bierlaire, M., 2004. Swiss value of travel time savings. European Transport Conference, 2004. [14]

Becker, G. S., 1965. A theory of the allocation of time. The Economic Journal 75, 493–517. [15]

Bierlaire, M., 2003. Biogeme: A free package for the estimation of discrete choice models. Proceedings of the 3rd Swiss Transportation Research Conference, www.strc.ch/Paper/bierlaire.pdf. [24]

Bierlaire, M., 2005. An introduction to biogeme (version 1.4). http://transp-or2.epfl.ch/biogeme/doc/tutorial.pdf. [24]

Burge, P., Rohr, C., 2004. DATIV: SP design: Proposed approach for pilot survey. Report, TetraPlan in cooperation with RAND Europe and Gallup A/S. [17]

De Borger, B., Fosgerau, M., 2008. The trade-off between money and travel time: A test of the theory of reference-dependent preferences. Journal of Urban Economics 64, 101–115. [24]

DeSerpa, A., 1971. A theory of the economics of time. The Economic Journal 81, 828–846. [15]

Eklöf, J., Karlsson, S., 1999. Testing and correcting for sample selection bias in discrete choice contingent valuation studies. Working Paper Series in Economics and Finance 171, Stockholm School of Economics, http://econpapers.repec.org/RePEc:hhs:hastef:0171. [16]

Fosgerau, M., 2007. Using nonparametrics to specify a model to measure the value of travel time. Transportation Research, Part A 41, 842–856. [21]

Fosgerau, M., Hjorth, K., Lyk-Jensen, S. V., 2007a. The Danish Value of Time Study: Final report. Report for the Danish Ministry of Transport, Danish Transport Research Institute. [14, 16, 17]

Fosgerau, M., Hjorth, K., Lyk-Jensen, S. V., 2007b. The Danish Value of Time Study: Results from experiment 1. Report for the Danish Ministry of Transport, Danish Transport Research Institute. [21, 22, 26]

Heckman, J., 1979. Sample selection bias as a specification error. Econometrica 47, 153–161. [16]

Hjorth, K., 2007. Differences in the value of travel time across transport modes: Self-selection or strategic behaviour? Master's Thesis, Department of Mathematical Sciences, University of Aarhus (In Danish). [26]

Horowitz, J. K., McConnell, K. E., 2002. A review of WTA/WTP studies. Journal of Environmental Economics and Management 44, 426–447. [22]

Jara-Díaz, S. R., 2003. On the goods-activities technical relations in the time allocation theory. Transportation 30, 245–260. [15]

Jara-Díaz, S. R., 2007. Transport Economic Theory. Elsevier, Amsterdam. [15]

Jara-Díaz, S. R., Guevara, C. A., 2003. Behind the subjective value of travel time savings: The perception of work, leisure and travel from a joint mode choice-activity model. Journal of Transport Economics and Policy 37, 29–46. [15, 16]

Jiang, M., Morikawa, T., 2004. Theoretical analysis on the variation of value of travel time savings. Transportation Research, Part A 38, 551–571. [15]

Mabit, S., Fosgerau, M., 2006. Controlling for sample selection in the estimation of the value of travel time. 11th International Conference on Travel Behaviour Research, 2006. [16]

Mackie, P., Fowkes, A., Wardman, W., Whelan, G., Nellthorp, J., Bates, J., 2003. Value of travel time savings in the UK – summary report. Report to Department for Transport. Institute for Transport Studies, University of Leeds, in association with John Bates Services. [14, 16]

Munizaga, M. A., Correia, R., Jara-Díaz, S. R., de Dios Ortúzar, J., 2006. Valuing time with a joint mode choice-activity model. International journal of transport economics 33, 193–210. [16]

Oort, O., 1969. The evaluation of travelling time. Journal of Transport Economics and Policy 3, 279–286. [15]

Ramjerdi, F., Sælensminde, K., Rand, L., Sætermo, I., 1997. Summary: The Norwegian value of time study, part 1. Report for the Norwegian Ministry of Transport and Communications, Institute of Transport Economics, Norwegian Centre for Transport Research, Oslo, Report no. 379/1997. [14]

Shires, J. D., de Jong, G. C., 2006. An international meta-analysis of values of time. Annex A for the HEATCO report *Deliverable 5: Proposal for Harmonised Guidelines*, heatco.ier.uni-stuttgart.de. [14]

Train, K., 2003. Discrete Choice Methods with Simulation. Cambridge University Press, http://elsa.berkeley.edu/books/choice2.html. [24]

Wardman, M., 1998. The value of travel time - a review of British evidence. Journal of Transport Economics and Policy 32, 285–316. [13]

Wardman, M., 2004. Public transport values of time. Transport Policy 11, 363–377. [13, 16]

Wartburg, M., Waters II, W. G., 2005. Congestion externalities and the value of travel time savings. In ”Towards Estimating the Social and Environmental Costs of Transportation in Canada – A report for Transport Canada”, Centre for Transportation Studies, University of British Columbia. [13]

Appendix

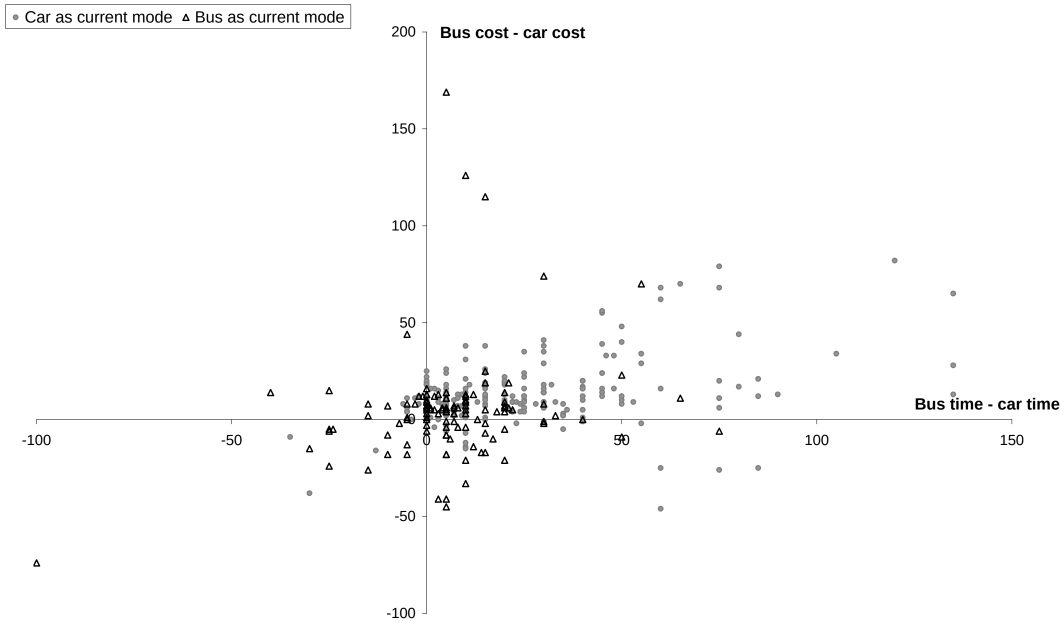

Figure 2.1: Differences in travel time and cost between reference trip and alternative reference trip - Respondents with car and bus as available modes (excluding four outliers)

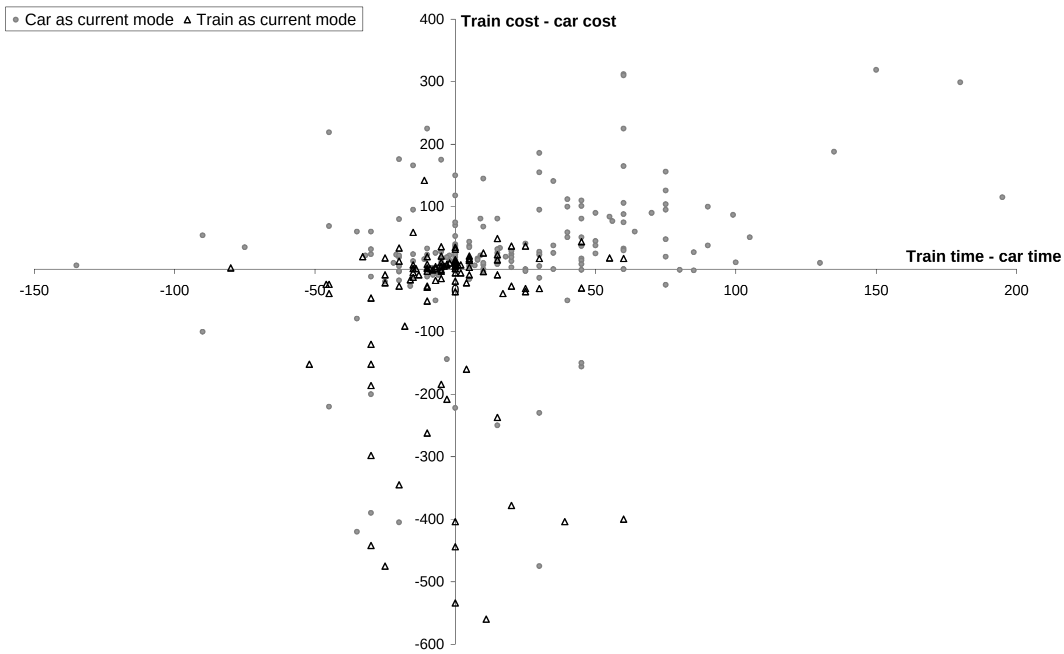

Figure 2.2: Differences in travel time and cost between reference trip and alternative reference trip - Respondents with car and train as available modes (excluding four outliers)

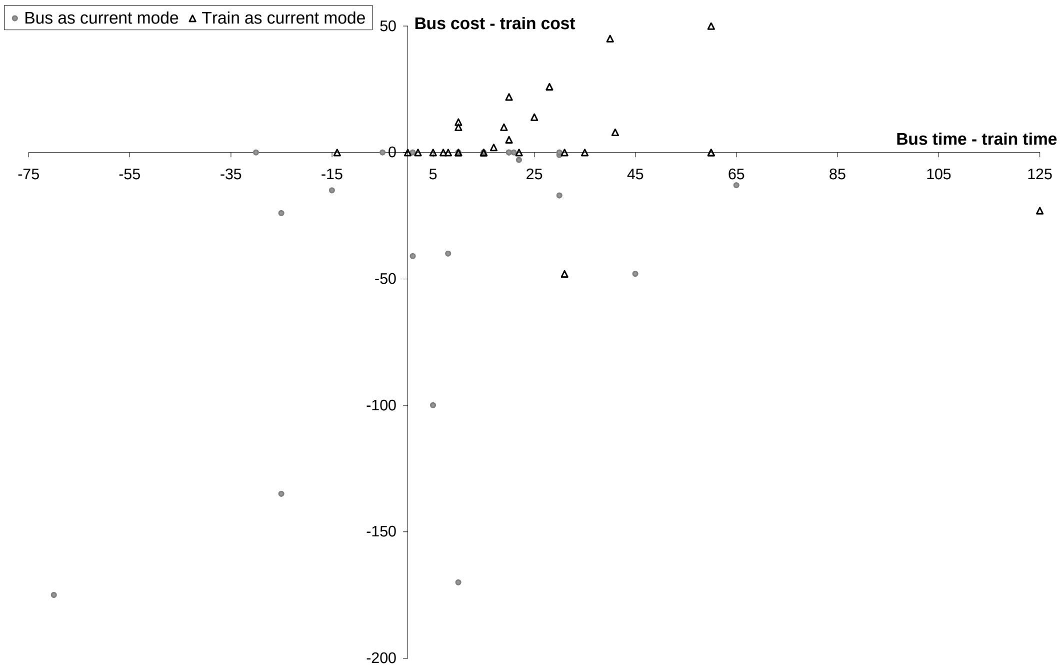

Figure 2.3: Differences in travel time and cost between reference trip and alternative reference trip - Respondents with bus and train as available modes (excluding a single outlier)

Table 2.5: Parameter estimates

Parameter	Estimate	Std.Err.	
δ^{CN1}	0.187	0.055	***
δ^{CB1}	0.308	0.092	***
δ^{CT1}	0.314	0.098	***
δ^{BC1}	−0.108	0.118	
δ^{BT1}	−0.234	0.260	
δ^{TN1}	0.311	0.065	***
δ^{TB1}	−0.319	0.234	
δ^{TC1}	0.372	0.123	***
δ^{CB2}	0.222	0.093	**
δ^{CT2}	0.443	0.100	***
δ^{BC2}	0.061	0.117	
δ^{BT2}	−0.337	0.260	
δ^{TB2}	−0.028	0.231	
δ^{TC2}	−0.060	0.124	
Constant	−0.609	0.113	***
σ	1.022	0.020	***
μ	1.547	0.022	***
β's corresponding to			
WTP	−0.252	0.025	***
WTA	0.378	0.024	***
EL	0.110	0.025	***
$\min(\Delta t - 15, 0)$	0.055	0.003	***
Commuter	0.149	0.049	***
Log (reference travel cost)	0.405	0.026	***
Log (reference travel time)	−0.386	0.034	***
Log (personal income)	0.601	0.063	***
Low income	0.501	0.097	***
Missing income	−0.143	0.078	*
Greater Copenhagen Area	0.086	0.046	*
Age 31-65	−0.211	0.054	***
Age 66+	−0.613	0.074	***
Female	−0.074	0.040	*
Log likelihood value		-17676.1	
Number of observations		36093	
Number of respondents		3945	

*** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level

Table 2.6: Likelihood ratio tests

Hypothesis	Log Like diff	Degrees of freedom	p-value
Current car drivers and current bus users have common VTT in car: $\delta^{CB1} = \delta^{BC2}$	1.7	1	0.07
Current car drivers and current bus users have common VTT in bus: $\delta^{CB2} = \delta^{BC1}$	2.9	1	0.02
Current car drivers and current train users have common VTT in car: $\delta^{CT1} = \delta^{TC2}$	3.4	1	0.01
Current car drivers and current train users have common VTT in train: $\delta^{CT2} = \delta^{TC1}$	0.2	1	0.53
Current bus users and current train users have common VTT in bus: $\delta^{BT1} = \delta^{TB2}$	0.2	1	0.53
Current bus users and current train users have common VTT in train: $\delta^{BT2} = \delta^{TB1}$	0.0	1	1.00
No mode effect among current bus users: $\delta^{BC1} = \delta^{BC2} = \delta^{BT1} = \delta^{BT2} = 0$	3.0	4	0.20
Train users with bus as alternative have common VTT in bus and train: $\delta^{TB1} = \delta^{TB2}$	1.4	1	0.09
Car drivers with bus as alternative have common VTT in car and bus: $\delta^{CB1} = \delta^{CB2}$	1.0	1	0.16
Car drivers with train as alternative have common VTT in car and train: $\delta^{CT1} = \delta^{CT2}$	2.2	1	0.04
Train users with car as alternative have common VTT in train and car: $\delta^{TC1} = \delta^{TC2}$	13.7	1	< 0.01

Chapter 3

Using prospect theory to investigate the low value of travel time for small time changes

Using prospect theory to investigate the low value of travel time for small time changes

Katrine Hjorth and Mogens Fosgerau

Abstract

A common finding in stated preference studies that measure the value of travel time (VTT), is that the measured marginal VTT increases with the size of the time change considered, in conflict with standard neoclassical theory. The current paper tests prospect theory as a possible explanation: More specifically, whether the phenomenon is generated by preferences being reference-dependent and exhibiting diminishing sensitivity for gains and losses, with a stronger degree of diminishing sensitivity for money than for travel time.

We use stated preference data with trade-offs between travel time and money that provide identification of the degrees of diminishing sensitivity for time and money gains and losses, thus enabling us to test and potentially falsify the prospect theory explanation. We apply a discrete choice model, in which choice depends on a reference-free value of travel time and reference-dependent value functions for time and money, allowing for loss aversion and different degrees of diminishing sensitivity for gains and losses. We use semi-parametric local logit estimates of the equi-probability curves in the data to test the model's appropriateness, and estimate its parameters using a mixed logit approach. Our results support the prospect theory explanation.

3.1 Introduction

An often encountered phenomenon in stated preference (SP) studies that measure the value of travel time (VTT), is that the measured marginal VTT increases with the size of the time change considered, in conflict with standard neoclassical theory (Gunn, 2001; Hultkrantz and Mortazavi, 2001; Mackie et al., 2001, 2003; Fosgerau et al., 2007). The effect is large enough to be of considerable economic significance (Mackie et al., 2003; Fosgerau et al., 2007), and problematic because it is inappropriate for evaluations of transport projects to apply a lower unit VTT for small time changes: This would cause evaluations to depend in an illogical way on whether the project was evaluated as a whole or as a series of smaller projects each resulting in smaller time savings (Fosgerau et al., 2007).

Several explanations to the phenomenon have been proposed (Mackie et al., 2003; Cantillo et al., 2006), but so far it remains a puzzle. Recently, De Borger and Fosgerau (2008) suggested prospect theory as a possible explanation, arguing that the phenomenon could be generated by preferences being reference-dependent and exhibiting diminishing sensitivity for gains and losses, with a stronger degree of diminishing sensitivity for money than for travel time. This explanation is supported by the fact that stated preference studies measuring the VTT until quite recently did not take reference-dependence into account.[1]

For the explanation to be valid, two conditions must hold: First, the reference-dependent model underlying the analysis in De Borger and Fosgerau (2008) must be an adequate description of the behaviour observed in the SP surveys. Second, the observed preferences should exhibit stronger diminishing sensitivity for money than for travel time. De Borger and Fosgerau (2008) provide empirical support for the latter condition, but only partly for the former, because they lack the data to separately identify the degrees of diminishing sensitivity for travel time and cost. The current paper extends their analysis, using data that provide better identification, and thus presents an empirical test with potential to falsify the prospect theory explanation.

Usually, the VTT is measured from SP data where respondents make choices between travel alternatives that differ with respect to travel time and cost. A common experimental setup is to use binary choices between a fast and expensive travel alternative and a slower and cheaper one. In recent studies, using electronic questionnaires, the time and cost attributes of the alternatives are varied around individual-specific reference values, corresponding to the normal or most recently experienced travel time and cost of the journey of interest (Burge et al., 2004; Fosgerau et al., 2007; de Jong et al., 2007; Ramjerdi et al., 2010). Table 3.1 presents four types of choices often applied in such VTT studies, using the following notation: Let t_1, t_2, c_1, c_2 be the travel time and cost attributes of the two alternatives, respectively, normalised by subtracting the reference values, such that negative values correspond to gains (faster or cheaper than reference) and positive values to losses (slower or more expensive than reference). Assume alternatives are sorted such that $t_1 < t_2$ and $c_1 > c_2$, and define $\Delta t := t_2 - t_1$ and $\Delta c := c_1 - c_2$. We use the notation from De Borger and Fosgerau (2008) and label the choice types WTP (willingness-to-pay), WTA (willingness-to-accept), EG (equivalent gain), and EL (equivalent loss). The choices are reference-based in the sense that they always have one time attribute equal to the reference time (i.e. $t_1 = 0$ or $t_2 = 0$) and one cost attribute equal to the reference cost (i.e. $c_1 = 0$ or $c_2 = 0$). [2]

In such a setting, if the reference values represent the respondent's perception of the normal travel time and cost, prospect theory suggests that the indirectly observed preferences may be reference-dependent (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991). In prospect theory, preferences are defined in terms of value functions, which have three general characteristics: *Reference-dependence:* the carriers of value are gains and losses relative to a reference point; *Loss aversion:* losses are valued

[1]Descriptive behavioural theories as prospect theory and rank-dependent utility theory have only recently been applied in travel behaviour research (see, e.g. Van de Kaa, 2008; Avineri and Bovy, 2008). To our knowledge, Van de Kaa (2005) was one of the first to argue that VTT studies should control for reference-dependence, preceded by a discussion of the gap between willingness-to-pay and willingness-to-accept in such studies. Recent VTT studies have allowed for reference-dependence in the form of loss aversion, whereas diminishing sensitivity for gains and losses is generally not accommodated.

[2]These choice types are applied in the national British (1994-96), Dutch (1988, 1997-98, 2007-), Danish (2004-2007) and Norwegian (2009) VTT studies (Burge et al., 2004; Fosgerau et al., 2007; de Jong et al., 2007; Ramjerdi et al., 2010). In addition, the Dutch and Norwegian studies included choices that were not reference-based. The national Swedish (1994) VTT study used a variation of the WTA and WTP choices (Burge et al., 2004).

Table 3.1: Reference-based choice types

	Fast alternative		Slow alternative	
Choice type	t_1	c_1	t_2	c_2
WTP	$-\Delta t$	Δc	0	0
WTA	0	0	Δt	$-\Delta c$
EL	0	Δc	Δt	0
EG	$-\Delta t$	0	0	$-\Delta c$

Note: $\Delta t, \Delta c > 0$ denote the time and cost differences between alternatives.

more heavily than gains; *Diminishing sensitivity:* the marginal value of both gains and losses decreases with their size.

De Borger and Fosgerau (2008) analyse data of the type presented in Table 3.1, using a choice model with reference-dependent preferences for travel time and money, based on prospect theory. They use a flexible functional form for the value functions for time and money, which permits the characteristics of prospect theory, but is more general. However, the authors are unable to identify value function curvature empirically (they can only identify the ratio of time and money curvature parameters) because their data only contain reference-based choice situations.

This paper extends their analysis by also using two types of non-reference-based choices, shown in Table 3.2. Here, both time attributes are different from the reference time. Using the modelling framework from De Borger and Fosgerau (2008), we formulate a discrete choice model, in which choice depends on the reference-free value of travel time and the value functions for time and cost. We test this parametric model by comparing its predicted equi-probability curves to those of the data, estimated using a semi-parametric local logit estimator (Fan et al., 1995; Fosgerau, 2007). Based on this test, we conclude that our data do not reject the parametric model.

The value functions are estimated from our parametric model using mixed logit estimation, and the results are consistent with prospect theory. In general, the value functions exhibit loss aversion for both travel time and cost, the value function for cost exhibits diminishing sensitivity for both gains and losses, and the value function for time exhibits constant sensitivity for both gains and losses. We find that the value function for cost "bends" more than the value function for time, i.e. there is stronger diminishing sensitivity for money than for travel time. Our results thus support prospect theory as an explanation of the phenomenon that the marginal VTT increases with the size of the time change.

The paper is organised as follows. Section 3.2 presents the model, section 3.3 our data, section 3.4 our analysis, and section 3.5 concludes.

Table 3.2: Non-reference-based (nrb) choice types

	Fast alternative		Slow alternative	
Choice type	t_1	c_1	t_2	c_2
EL-nrb	t'	Δc	$t'+\Delta t$	0
EG-nrb	$-t'-\Delta t$	0	$-t'$	$-\Delta c$

Note: $\Delta t, \Delta c > 0$ denote the time and cost differences between alternatives. $t' > 0$ denotes the shift off the reference.

3.2 Model

3.2.1 Parametric model

Our setting is similar to the one in De Borger and Fosgerau (2008): We consider binary choices between two travel alternatives that differ with respect to travel time and cost, such that one alternative is faster but more expensive than the other. Individuals have a reference travel time t_0 and a reference cost c_0, representing their normal state. As above, t_1, t_2, c_1, c_2 denote the travel time and cost attributes of the two alternatives, respectively, normalised by subtracting the reference values, and alternatives are sorted such that $t_1 < t_2$ and $c_1 > c_2$.

Assume we observe the six different types of choices given in Tables 3.1 and 3.2. We assume that individuals prefer the slow alternative (alternative 2) whenever [3]

$$wv_t(t_1) + v_c(c_1) < wv_t(t_2) + v_c(c_2), \tag{3.1}$$

where w is a reference-free marginal value of travel time (the absolute value of the reference-free marginal rate of substitution between travel time and money), which varies randomly in the population, and v_t, v_c are value functions for travel time and cost, that measure the values the individuals assign to the time and cost attributes.[4] As De Borger and Fosgerau (2008), we assume the value functions have the following form: [5]

$$v_t(t) = -|t|^{1-\beta_t+\gamma_t S(t)} S(t) e^{\eta_t S(t)}, \tag{3.2}$$

$$v_c(c) = -|c|^{1-\beta_c+\gamma_c S(c)} S(c) e^{\eta_c S(c)}. \tag{3.3}$$

$S(\cdot)$ is the sign function, which takes the values 1, 0, and -1, when its argument is positive, zero, and negative, respectively. The parameters η, β, and γ determine the slope and curvature of the value functions. Equations (3.2) and (3.3) are flexible formulations, allowing for a range of possible shapes. In order to make the derivations following below, we require the value functions to be decreasing, such that higher travel time or cost

[3] Unlike De Borger and Fosgerau (2008), we do not put w inside the value function for travel time.

[4] The term "value function" stems from prospect theory (Kahneman and Tversky, 1979).

[5] This is a two-part power function with separate slopes and exponents for gains and losses, as is often applied in studies based on prospect theory, though parameterised slightly differently. The power functional form has been criticized, because the measured degree of loss aversion depends on the scaling of the attributes (see e.g. Wakker, 2010); it has however, in the few comparisons available, been found to have empirical support in terms of better goodness-of-fit (Stott, 2006).

makes an alternative less attractive. This corresponds to $\beta - 1 < \gamma < 1 - \beta$. The value functions exhibit diminishing sensitivity to gains if $-\beta < \gamma$, and to losses if $\gamma < \beta$. If $\gamma > 0$, the value function exhibits a higher degree of diminishing sensitivity to gains than to losses (it "bends" more in the gain region) – if $\gamma < 0$, the opposite is the case.

We say that the value functions exhibit loss aversion if the numerical value of a loss exceeds the numerical value of a gain of the same size, i.e. if $v_t(-|t|) < |v_t(|t|)|$, respectively $v_c(-|c|) < |v_c(|c|)|$. If $\gamma = 0$, loss aversion is equivalent to $\eta > 0$. If $\gamma > 0$, the value function exhibits loss aversion for all time/cost changes larger than $\exp(-\eta/\gamma)$, while if $\gamma < 0$, we have loss aversion for all time/cost changes smaller than $\exp(-\eta/\gamma)$.

For the choice types in our data, it is always the case that

- either $c_1 = 0$ or $c_2 = 0$,

and

- either $t_1 = 0$ or $t_2 = 0$ or $S(t_1) = S(t_2)$.

Applying this with the value functions in equations (3.2) and (3.3), and taking logs, we see that eq. (3.1) is equivalent to

$$\begin{aligned} \log w < {} & \eta_c S(c_1 + c_2) - \eta_t S(t_1 + t_2) \\ & + \log\left[S(c_1+c_2)(|c_1|^{1-\beta_c+\gamma_c S(c_1+c_2)} - |c_2|^{1-\beta_c+\gamma_c S(c_1+c_2)})\right] \\ & - \log\left[S(t_1+t_2)(|t_2|^{1-\beta_t+\gamma_t S(t_1+t_2)} - |t_1|^{1-\beta_t+\gamma_t S(t_1+t_2)})\right]. \end{aligned} \tag{3.4}$$

Note that the terms in square brackets are always positive, so that the logarithms are well-defined. Let $y = 1_{\{\text{slow alt chosen}\}}$, i.e. y takes the value 1 when the slow alternative is chosen, and the value 0 otherwise. To take into account that individuals may make errors when comparing alternatives in the questionnaire, we do not assume that individuals choose the slow alternative whenever eq. (3.4) holds, but only that people do not deviate systematically from this rule. More specifically, we assume that

$$\begin{aligned} & y = 1 \\ & \Updownarrow \\ & \log w + \varepsilon < \eta_c S(c_1 + c_2) - \eta_t S(t_1 + t_2) \\ & \qquad + \log\left[S(c_1+c_2)(|c_1|^{1-\beta_c+\gamma_c S(c_1+c_2)} - |c_2|^{1-\beta_c+\gamma_c S(c_1+c_2)})\right] \\ & \qquad - \log\left[S(t_1+t_2)(|t_2|^{1-\beta_t+\gamma_t S(t_1+t_2)} - |t_1|^{1-\beta_t+\gamma_t S(t_1+t_2)})\right], \end{aligned} \tag{3.5}$$

where ε is a symmetric random error with mean zero, independently and identically distributed across individuals and choices.

3.2.2 Equi-probability curves for WTP, WTA, EG, and EL choices

For the choice types WTP, WTA, EG, and EL, the choice probabilities have nice functional forms. For these choice types, we always have that $t_1 = 0$ or $t_2 = 0$, which implies

Table 3.3: Slopes and intercepts of equi-probability curves with prob. p in $(\log\Delta t, \log\Delta c)$-space.

Choice type	Slope	Intercept
WTP	$\frac{1-\beta_t-\gamma_t}{1-\beta_c+\gamma_c}$	$\frac{F^{-1}(p)-\eta_c-\eta_t}{1-\beta_c+\gamma_c}$
WTA	$\frac{1-\beta_t+\gamma_t}{1-\beta_c-\gamma_c}$	$\frac{F^{-1}(p)+\eta_c+\eta_t}{1-\beta_c-\gamma_c}$
EL	$\frac{1-\beta_t+\gamma_t}{1-\beta_c+\gamma_c}$	$\frac{F^{-1}(p)-\eta_c+\eta_t}{1-\beta_c+\gamma_c}$
EG	$\frac{1-\beta_t-\gamma_t}{1-\beta_c-\gamma_c}$	$\frac{F^{-1}(p)+\eta_c-\eta_t}{1-\beta_c-\gamma_c}$

that the probability of choosing the slow alternative can be written as a function of Δt, Δc, and F, the cumulative distribution function (CDF) of $\log w + \varepsilon$. Assume that $\log w + \varepsilon$ is an absolutely continuous random variable, such that F has an inverse. Then for WTP choices, where $t_2 = 0$ and $c_2 = 0$, we have that

$$\begin{aligned} p &= P(y = 1|\Delta t, \Delta c) \\ &= F\left(\eta_c + \eta_t + (1-\beta_c+\gamma_c)\log\Delta c - (1-\beta_t-\gamma_t)\log\Delta t\right) \end{aligned}$$

$$\Updownarrow$$

$$\log\Delta c = \frac{F^{-1}(p)-\eta_c-\eta_t}{1-\beta_c+\gamma_c} + \frac{1-\beta_t-\gamma_t}{1-\beta_c+\gamma_c}\log\Delta t. \tag{3.6}$$

Hence the equi-probability curves in $(\log\Delta t, \log\Delta c)$-space, i.e. the sets $\{(\log\Delta t, \log\Delta c) \in \mathbb{R}^2 | P(y = 1|\Delta t, \Delta c) = p\}$ for different values of $p \in]0,1[$, are parallel straight lines. This is also the case for WTA, EG, and EL choices. Table 3.3 lists the slopes and intercepts for all four choice types.

Assume that the value functions are decreasing, i.e. that $\beta_t - 1 < \gamma_t < 1 - \beta_t$ and $\beta_c - 1 < \gamma_c < 1 - \beta_c$. This implies that the equi-probability curves have positive slopes, cf. Table 3.3. If $\gamma_t > 0$, the equi-probability curves will be steeper for EL than WTP choices, and steeper for WTA than EG choices. If $\gamma_c > 0$, the curves are steeper for EG than WTP choices, and steeper for WTA than EL choices. Moreover, loss aversion in the travel time dimension is equivalent to the equi-probability curve for EL being above that for WTP for a given value of p, and to the equi-probability curve for WTA being above that for EG.

3.2.3 Consequences of ignoring reference-dependence: A positive relation between the marginal VTT and Δt

Suppose we could observe choices without any measurement error, and that everybody in the population had identical preferences and behaved according to equations (3.1), (3.2), and (3.3). What would happen if we tried to measure the VTT from standard data as the choice types in Table 3.1, but did not take reference-dependence into account?

Let $\Delta t > 0$ denote a given time change, and consider the elicitation measure $WTP(\Delta t)$, defined as the cost change $\Delta c > 0$ that would make respondents indifferent between the two alternatives in a WTP choice. This measure is one possible estimate of the VTT. From equations (3.1), (3.2), and (3.3), it follows that (cf. the results in De Borger and Fosgerau, 2008):

$$WTP(\Delta t) = \left(we^{-\eta_t-\eta_c}\Delta t^{1-\beta_t-\gamma_t}\right)^{1/(1-\beta_c+\gamma_c)}.$$

Defining $WTA(\Delta t)$, $EL(\Delta t)$, and $EG(\Delta t)$ similarly, we find that:

$$\begin{aligned}
WTA(\Delta t) &= \left(we^{\eta_t+\eta_c}\Delta t^{1-\beta_t+\gamma_t}\right)^{1/(1-\beta_c-\gamma_c)}\\
EL(\Delta t) &= \left(we^{\eta_t-\eta_c}\Delta t^{1-\beta_t+\gamma_t}\right)^{1/(1-\beta_c+\gamma_c)}\\
EG(\Delta t) &= \left(we^{-\eta_t+\eta_c}\Delta t^{1-\beta_t-\gamma_t}\right)^{1/(1-\beta_c-\gamma_c)}
\end{aligned}$$

We see that the corresponding estimates of the marginal VTT ($WTP(\Delta t)/\Delta t$, $WTA(\Delta t)/\Delta t$, $EL(\Delta t)/\Delta t$ and $EG(\Delta t)/\Delta t$) would depend on Δt, even if w (the reference-free marginal VTT) were constant. In particular, if the value function for cost bends more than the value function for time, i.e. if $(1-\beta_t-\gamma_t)/(1-\beta_c+\gamma_c) > 1$, $(1-\beta_t+\gamma_t)/(1-\beta_c-\gamma_c) > 1$, $(1-\beta_t+\gamma_t)/(1-\beta_c+\gamma_c) > 1$, and $(1-\beta_t-\gamma_t)/(1-\beta_c-\gamma_c) > 1$, the estimate of the marginal VTT is increasing in Δt for all four measures. This implies that if we estimate the VTT by one of the four measures (or a combination), we would observe a marginal VTT increasing in the size of the time change, even if the common reference-free marginal value of time, w, were constant.

3.3 Data

Our data stem from a Norwegian survey conducted to establish values of travel time, variability, and traffic safety to be used in welfare-economic evaluations of transport infrastructure policies (Samstad et al., 2010; Ramjerdi et al., 2010). The respondents were recruited from a representative panel, and the survey was carried out on the Internet.

The survey covered both car trips, public transport (PT) trips and plane trips. In our analysis, we consider five combinations of transport mode and distance, which we analyse separately:

- Car short - car trips less than 100 km
- PT short - public transport trips less than 100 km
- Car long - car trips longer than 100 km
- PT long - public transport trips longer than 100 km
- Air - domestic plane trips

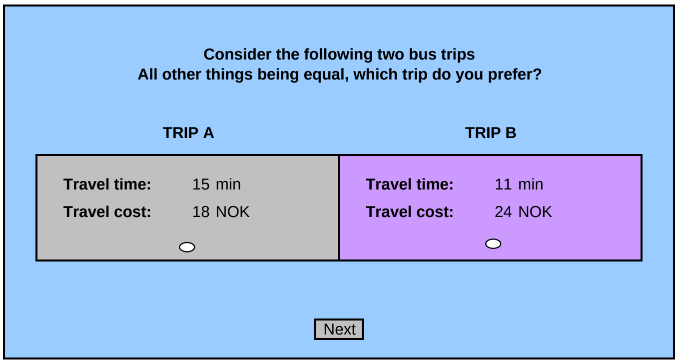

Figure 3.1: Illustration of choice

The survey contained several stated preference experiments, of which we use one: The choice experiment consists of nine binary choices between travel alternatives that differ with respect to cost and travel time, as illustrated in Figure 3.1. Always, one alternative is faster and more expensive than the other. The time and cost attributes are pivoted around the travel time (t_0) and cost (c_0) of a reference trip which the respondents reported at the beginning of the survey. The reference trip is a one-way domestic trip for private purpose, carried out within the last week (for short distance segments) or within the last month (for long distance segments). Travel time is defined as in-vehicle time without stops, except for air travellers, where travel time is measured from airport to airport. The choices are of the types shown in Tables 3.1 and 3.2. Eight of the nine choices are reference-based (two WTP choices, two WTA choices, two EG choices, two EL choices), and one choice is non-reference-based (either EG-nrb or EL-nrb).

In our analysis, we exclude respondents who answered side-lexicographically (always chose left or right alternative), dropped out during the survey, or gave unrealistic reference values.[6] We also exclude air travellers with a reference travel time less than 80 minutes, because of an error in the questionnaire. These exclusions correspond to 7-9% of the observations for the car short, car long and PT long segments, and around 16-18% of the observations for air and PT short. Moreover, data are sparse for high values of reference time and cost, so we restrict our analysis to the following samples:[7]

- Car short: Cost $\leq$ 250 NOK, time $\leq$ 90 minutes.
- PT short: Cost $\leq$ 100 NOK, time $\leq$ 90 minutes.
- Car/PT long: Cost $\leq$ 1500 NOK, time $\leq$ 900 minutes.
- Air: Cost $\leq$ 5000 NOK, time $\leq$ 600 minutes, distance $\leq$ 3000 km.

Table 3.4 lists the resulting sample sizes. The sample is close to being balanced, with only 5 individuals (in the car segments) missing a few observations each. As we explain

[6] Unrealistic values are average speeds above 100 km per hour for land modes, average speeds above 1000 km per hour for air, costs less than 50 NOK for long distance modes, cost per kilometre less than 0.2 NOK or higher than 11 NOK for car modes.

[7] 1 NOK $\approx$ 0.12 Euro.

Table 3.4: Samples

Segment	Individuals	Obs	Reference-based obs
Car short	3019	27163	24144
PT short	547	4923	4376
Car long	1130	10169	9039
PT long	940	8460	7520
Air	758	6822	6064

in section 3.4.3, our parametric analysis uses only a subsample, trimming data at the 5% and 95% quantiles of Δt and Δc, which causes the samples to become more unbalanced. Table 3.8 in the Appendix provides summary information of the subsample used in our parametric analysis.

3.4 Analysis

3.4.1 Semi-parametric model validation

As a check of the parametric model in eq. (3.5), we estimate the equi-probability curves in the data and compare to those of the model. We do this separately for each data segment and choice type. To estimate the choice probabilities $P(y=1|\Delta t,\Delta c)$ as function of Δt and Δc, we use the semi-parametric framework from Fosgerau (2007), which is based on Fan et al. (1995): Let $\{(y_i,\Delta t_i,\Delta c_i)\}_{i=1}^{N}$ denote the sample of interest, and let Γ be the CDF of the standard logistic distribution. For a given point $(\Delta t,\Delta c)$, the choice probability $P(y=1|\Delta t,\Delta c)$ is estimated by the Local Logit Kernel estimator $\Gamma(\hat{\alpha}_0)$, where

$$(3.7)\qquad (\hat{\alpha}_0,\hat{\alpha}_t,\hat{\alpha}_c)=\arg\max_{(\alpha_0,\alpha_t,\alpha_c)}\sum_{i=1}^{N}K_h(\Delta t_i-\Delta t,\Delta c_i-\Delta c)\log P_i(\alpha_0,\alpha_t,\alpha_c),$$

P_i is the logit choice probability

$$\begin{aligned}P_i(\alpha_0,\alpha_t,\alpha_c)=&\left(\Gamma(\alpha_0+\alpha_t(\Delta t_i-\Delta t)+\alpha_c(\Delta c_i-\Delta c))\right)^{y_i}\\ &\cdot\left(1-\Gamma(\alpha_0+\alpha_t(\Delta t_i-\Delta t)+\alpha_c(\Delta c_i-\Delta c))\right)^{1-y_i},\end{aligned}$$

and $K_h(\cdot,\cdot)$ is a two-dimensional kernel with bandwidth h.

The estimations are carried out in Ox (Doornik, 2001), using a triangular kernel and manually chosen bandwidths. In areas where the data are sparse, the bandwidth is increased to ensure that at least 15 observations are used in each local estimation. For computational convenience, we use the same bandwidths in both time and cost dimensions.

3.4.2 Parametric model estimation

We estimate the parameters in our model using maximum likelihood mixed logit estimation of eq. (3.5): The error term ε is assumed to be logistic with mean zero and scale parameter μ (inversely proportional to the standard deviation). Log w is assumed to be individual-specific and to have a Normal distribution in the population, with standard deviation σ. This allows for unobserved heterogeneity in the VTT (note that we do not control for any observed heterogeneity, as no explanatory variables are included). We estimate a model (MXL1) with γ_t, γ_c fixed to zero, and another (MXL2) with γ_t, γ_c being free parameters. In the restricted model (MXL1), the value functions have the same curvature for gains and losses, so the entire gain-loss discrepancy is captured by the difference in levels (the η's). As a robustness check, we also estimate plain logit models, where $\log w$ is assumed to be constant.

We estimate a separate set of parameter values for each of the five data segments. Estimations are carried out in Biogeme (Bierlaire, 2003, 2005), using 500 Halton draws to simulate the individual-specific effect (see e.g. Train, 2003, for a definition).

3.4.3 Results

Semi-parametric analysis

We first regress y on Δt and Δc (as described in section 3.4.1). The distributions of Δt and Δc in the data have rather long right tails, implying that estimates of $P(y=1|\Delta t, \Delta c)$ will be very unreliable for high values of Δt and Δc. Initially, we therefore only use observations where Δt and Δc are below their 90% quantiles. Figure 3.2 shows the estimated equi-probability curves for the car short segment, depicted in $(\log \Delta t, \log \Delta c)$-space. The bandwidth is chosen manually by graphical inspection of the estimates: Our criterion is to find the smallest possible bandwidth yielding smooth, non-decreasing and non-backward-bending equi-probability curves. For the car short segment, we find that a bandwidth of 0.10 is suitable (for interpretation, note that the unit of Δt and Δc are minutes and NOK, respectively).

Second, we regress y directly on $\log \Delta t$ and $\log \Delta c$. This does not produce identical results, because regressing in log space corresponds to applying smaller bandwidths for low values of Δt and Δc and higher bandwidths for higher values. Regression in log space therefore yields more uncertain estimates in the low range of Δt and Δc. To account for this, we trim data both from below (at the 5% quantiles) and from above (at the 95% quantiles). Figure 3.3 shows the results for the car short segment, where we find that a bandwidth of 0.15 is suitable.

As shown, the equi-probability curves for the car short segment are roughly linear, in the sense that they do not deviate systematically from linearity, except in the upper left and lower right corners where data are sparse. We find similar results for the long distance segments (not shown here): the curves are roughly linear, again excepting the upper left and lower right corners. For PT short (not shown), the pattern is less clear: Curves are not as close to linear as for the other segments, but on the other hand it is hard to find a systematic deviation from linearity. Overall, we conclude that data between the 5% and 95% quantiles do not reject the parametric model in eq. (3.5).

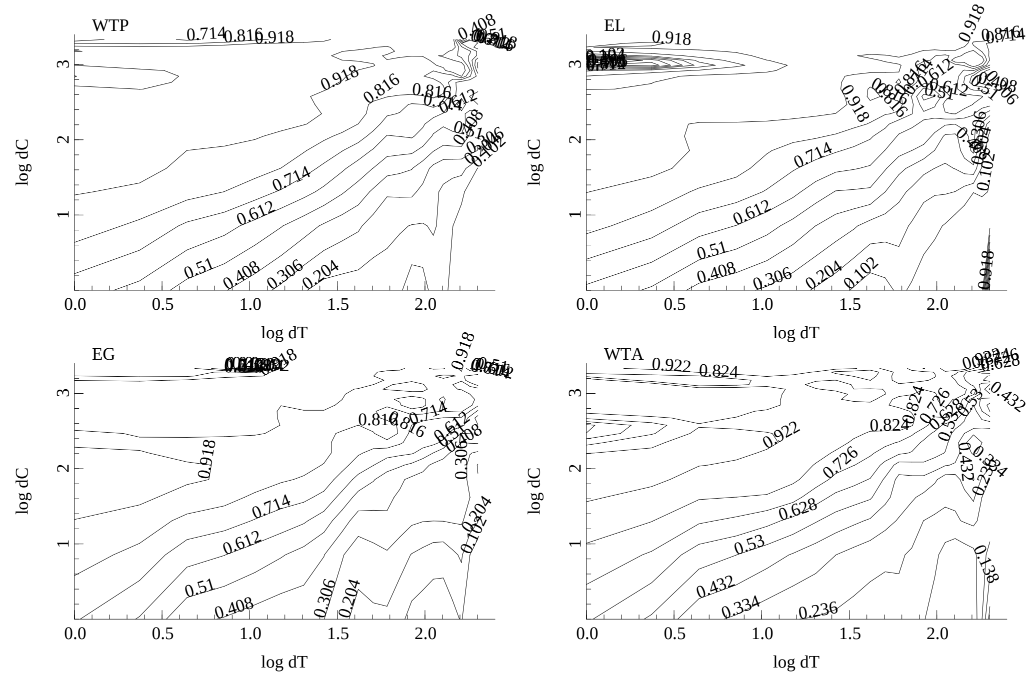

Figure 3.2: Equi-probability curves (local logit estimates), estimated on $(\Delta t, \Delta c)$. Car short, excluding top 10% in both dimensions. The figures along the curves denote probability levels.

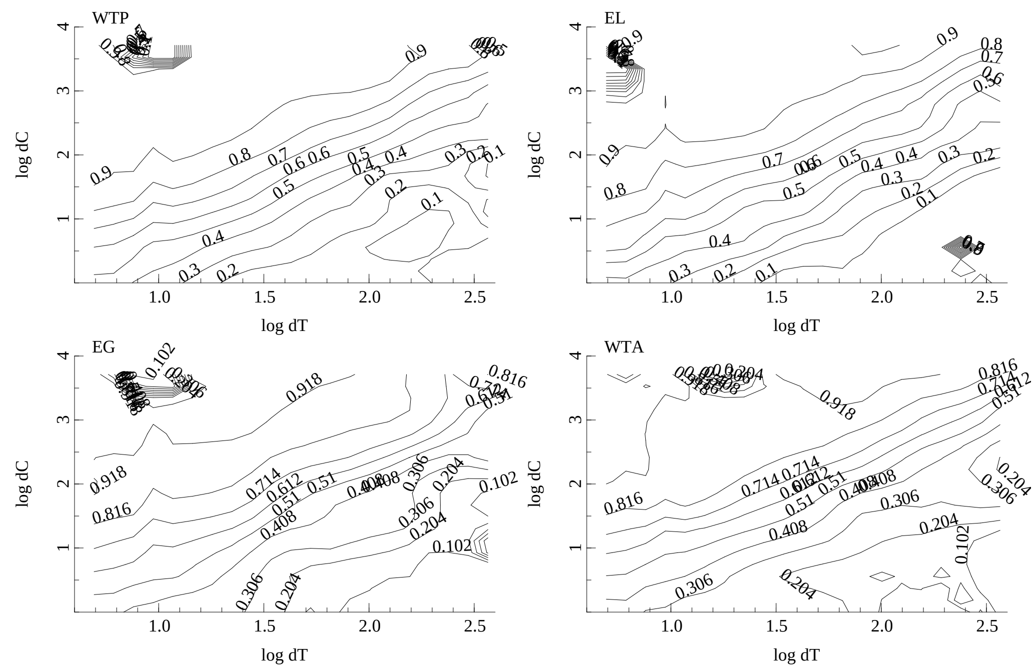

Figure 3.3: Equi-probability curves (local logit estimates), estimated on $(\log \Delta t, \log \Delta c)$. Car short, excluding top 5% and bottom 5% in both dimensions. The figures along the curves denote probability levels.

Table 3.5: Estimation Summary – Mixed Logit models (MXL1). Parameter estimates with robust standard errors in parentheses.

	Car short	PT short	Car long	PT long	Air
mean $(\log w)$	-0.46^*	-0.64^*	-0.22	-0.27^*	0.10
	(0.03)	(0.08)	(0.12)	(0.11)	(0.17)
β_c	0.19^*	0.03	0.21^*	0.15^*	0.16^*
	(0.02)	(0.08)	(0.04)	(0.04)	(0.05)
β_t	-0.02	-0.13^*	-0.03	-0.04	-0.06
	(0.02)	(0.06)	(0.03)	(0.03)	(0.04)
η_c	0.05^*	0.15^*	0.09^*	0.07^*	-0.01
	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)
η_t	0.06^*	0.05^*	0.09^*	0.05^*	0.03^*
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
σ	0.78^*	0.83^*	0.69^*	0.64^*	0.71^*
	(0.03)	(0.08)	(0.04)	(0.03)	(0.05)
μ	3.07^*	2.75^*	2.91^*	3.44^*	3.30^*
	(0.10)	(0.23)	(0.16)	(0.18)	(0.21)
Log likelihood value	-9563.1	-1681.3	-3705.8	-2999.8	-2406.2
Number of est. parameters	7	7	7	7	7
Number of obs.	23892	4375	8514	7023	5739

* denotes significance at the 5% level.

Parametric analysis

Based on the semi-parametric results, we limit the analysis to data between the 5% and 95% quantiles. Tables 3.5 and 3.6 present the parameter estimates. The MXL1 and MXL2 models yield practically identical value functions, so we only show the estimated value functions for the MXL2 models (Figures 3.4 – 3.6). The plain logit estimates are very similar to the mixed logit results (see Tables 3.9 and 3.10 in the Appendix), except for PT long, where the value function for cost bends more for the mixed logit model than for the logit model.

There is some variation in estimates between segments. Roughly speaking, the pattern seems to be that β_c and γ_c are significantly positive (5% level), β_t and γ_t are not significantly different from zero, and η_c and η_t are significantly positive in MXL1, but tend to become insignificant in MXL2.

From Figures 3.4 – 3.6 we see that the estimated value functions are decreasing, and that they appear to be close to piece-wise linear in the considered ranges (i.e. close to linear in the gain domain and close to linear in the loss domain). Though it appears close to piece-wise linear, the value function for cost exhibits diminishing sensitivity with respect to both gains and losses for all segments except PT short. This is significant in the sense that we can reject linearity of the value functions in both gain and loss domains (LR tests, 5% level, cf. Table 3.11 in the Appendix). For PT short, the value function for

Table 3.6: Estimation Summary – Mixed Logit models (MXL2). Parameter estimates with robust standard errors in parentheses.

	Car short	PT short	Car long	PT long	Air
mean $(\log w)$	-0.46^*	-0.64^*	-0.20	-0.28^*	0.10
	(0.03)	(0.08)	(0.13)	(0.11)	(0.17)
β_c	0.19^*	0.02	0.20^*	0.15^*	0.16^*
	(0.02)	(0.08)	(0.04)	(0.04)	(0.05)
β_t	-0.02	-0.13^*	-0.03	-0.04	-0.06
	(0.02)	(0.06)	(0.03)	(0.03)	(0.04)
η_c	0.01	0.06	-0.15^*	-0.13	-0.02
	(0.01)	(0.05)	(0.07)	(0.07)	(0.10)
η_t	0.07^*	0.10	0.02	-0.06	0.03
	(0.02)	(0.06)	(0.07)	(0.07)	(0.10)
γ_c	0.02^*	0.05^*	0.05^*	0.05^*	0.00
	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)
γ_t	-0.01	-0.03	0.02	0.03	0.00
	(0.01)	(0.03)	(0.02)	(0.02)	(0.03)
σ	0.78^*	0.83^*	0.69^*	0.64^*	0.71^*
	(0.03)	(0.08)	(0.04)	(0.03)	(0.05)
μ	3.07^*	2.74^*	2.88^*	3.41^*	3.30^*
	(0.10)	(0.24)	(0.16)	(0.18)	(0.21)
Log likelihood value	-9558.5	-1678.2	-3698.3	-2993.4	-2406.2
Number of est. parameters	9	9	9	9	9
Number of obs.	23892	4375	8514	7023	5739

* denotes significance at the 5% level.

cost does not exhibit diminishing sensitivity for losses, but is not significantly different from linear in this domain (LR test, 5% level, cf. Table 3.11).

The value function for time does not exhibit diminishing sensitivity in either direction. However, it is generally not significantly different from linear in neither gain nor loss domain (LR tests, 5% level, cf. Table 3.11), the exception being PT long (loss domain), where the difference is marginally significant, and PT short (gain domain).

For the short distance segments, we have loss aversion (defined as $v_t(-|t|) < |v_t(|t|)|$ and $v_c(-|c|) < |v_c(|c|)|$) for the considered ranges of both time and cost. Loss aversion is significant in the sense that LR tests of the hypotheses of no gain-loss asymmetry in the time dimension ($v_t(-|t|) = |v_t(|t|)|$ for all t, corresponding to $\eta_t = \gamma_t = 0$) and no gain-loss asymmetry in the cost dimension ($v_c(-|c|) = |v_c(|c|)|$ for all c, corresponding to $\eta_c = \gamma_c = 0$) are both rejected at the 5% level, cf. Table 3.11. For the car long and PT long segments, we have loss aversion in the time dimension for the considered range of time changes, and loss aversion in the cost dimension, for cost changes larger than 15 NOK. Again the gain-loss asymmetry is significant in both dimensions (LR tests of the hypotheses of no asymmetry are rejected at the 5% level, cf. Table 3.11).

For air, we have loss aversion in the time dimension for the considered range of time changes, but the gain-loss asymmetry is only significant at the 10% level (cf. Table 3.11). We do not observe loss aversion in the cost dimension, where gains are valued higher than losses for all cost changes. Here, however, the gain-loss asymmetry is not significant (the LR test of the hypothesis of no asymmetry cannot be rejected, cf. Table 3.11).

Overall, these results are consistent with prospect theory: With few exceptions, the estimated value functions either exhibit loss aversion and diminishing or constant sensitivity for gains and losses, or do not deviate significantly from this.

Moreover, the results support De Borger and Fosgerau (2008)'s proposed explanation of the positive relation between the VTT and the size of the time change, since we have $(1-\beta_t-\gamma_t)/(1-\beta_c+\gamma_c) > 1$, $(1-\beta_t+\gamma_t)/(1-\beta_c-\gamma_c) > 1$, $(1-\beta_t+\gamma_t)/(1-\beta_c+\gamma_c) > 1$, and $(1-\beta_t-\gamma_t)/(1-\beta_c-\gamma_c) > 1$.[8] Hence the value function for cost "bends" more than the value function for time, i.e. there is stronger diminishing sensitivity for money than for travel time. This implies that we would observe a marginal value of travel time increasing in the size of the time change, if we did not take reference-dependence into account.

As a final check, we compare our results to those of De Borger and Fosgerau (2008). In Table 3.7, we compute the parameters $p_5 = \frac{\gamma_t}{1-\beta_t}$, $p_6 = \frac{\eta_c}{1-\beta_t}$, $p_7 = \frac{1-\beta_c}{1-\beta_t}$, and $p_8 = \frac{\gamma_c}{1-\beta_t}$, which correspond to the estimated parameters in De Borger and Fosgerau (2008).[9] The results from MXL1 should be compared to their M3R (γ_t, γ_c fixed to zero), and the results from MXL2 should be compared to their M4R.

De Borger and Fosgerau (2008) find p_5 to be significantly positive, while our estimate is never significantly different from zero. For the short distance segments, p_6 is comparable in size and sign, though not significantly positive in the MXL2 models.

[8]This is also the case for the plain logit estimates.

[9]We cannot compare our estimate of η_t directly, since we apply a slightly different model: De Borger and Fosgerau (2008) have w inside the value function for time in eq. (3.1).

Table 3.7: Comparison to De Borger and Fosgerau (2008)'s results. MXL1 results should be compared to their M3R, and MXL2 results to their M4R.

Segment	Model	$p_5 = \frac{\gamma_t}{1-\beta_t}$	$p_6 = \frac{\eta_c}{1-\beta_t}$	$p_7 = \frac{1-\beta_c}{1-\beta_t}$	$p_8 = \frac{\gamma_c}{1-\beta_t}$
Car short	MXL1		0.05*	0.80*	
PT short	MXL1		0.13*	0.86*	
Car long	MXL1		0.09*	0.77*	
PT long	MXL1		0.07*	0.82*	
Air	MXL1		−0.01	0.79*	
De Borger and Fosgerau	M3R		0.15*	0.70*	
Car short	MXL2	−0.01	0.01	0.80*	0.02*
PT short	MXL2	−0.03	0.05	0.86*	0.05*
Car long	MXL2	0.02	−0.14*	0.78*	0.05*
PT long	MXL2	0.03	−0.13	0.82*	0.05*
Air	MXL2	0.00	−0.01	0.79*	0.00
De Borger and Fosgerau	M4R	0.035*	0.09*	0.70*	0.044*

* denotes significance at the 5% level. For our results, significance tests are based on the Delta method

For the long distance segments, our estimates of p_6 differ from those of De Borger and Fosgerau (2008): For car and PT, we find that p_6 is positive in MXL1, and negative in MXL2, while for air p_6 is never significantly different from zero. The variable p_7 is comparable in size and sign (for our results, all 95% confidence intervals are within [0.72, 0.95]), while p_8 is comparable in size and sign for all segments except air. Overall, our results for the short distance segments are in agreement with De Borger and Fosgerau (2008)'s results, while our results for the long distance segments agree to some degree.[10]

[10]For comparison, De Borger and Fosgerau (2008)'s sample consists of both short and long car trips, with a large majority of trips being shorter than 100 km.

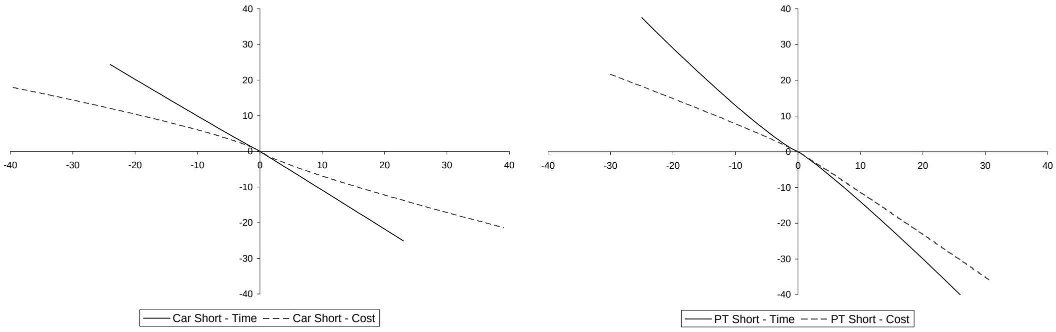

Figure 3.4: Value functions for car short and PT short. Value functions are depicted for the range where they are supported by the data.

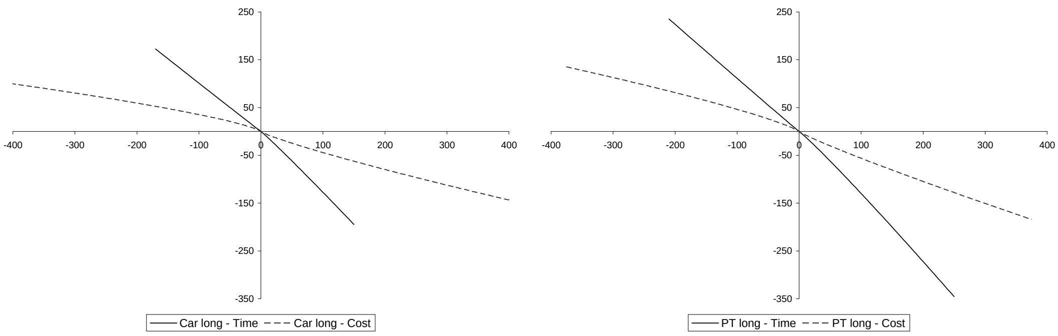

Figure 3.5: Value functions for car long and PT long. Value functions are depicted for the range where they are supported by the data (except for car long - cost, which has wider support)

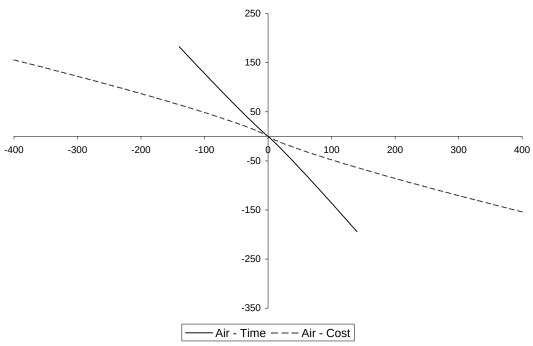

Figure 3.6: Value functions for air. Value functions are depicted for the range where they are supported by the data (except for cost, which has wider support)

3.5 Conclusion

The current paper extends the analysis in De Borger and Fosgerau (2008) and presents an empirical test with potential to falsify their proposed explanation to the phenomenon of the marginal VTT increasing with the size of the time change: That respondents have reference-dependent preferences that exhibit diminishing sensitivity for gains and losses, with a stronger degree of diminishing sensitivity for money than for travel time.

We used stated preference data with trade-offs between travel time and money that provide identification of the degrees of diminishing sensitivity for time and money gains and losses. Based on the modelling framework in De Borger and Fosgerau (2008) we formulated a parametric discrete choice model, in which choice depends on a reference-free marginal value of travel time and reference-dependent value functions for time and money. The functional form of the value functions allows, but is not restricted to, loss aversion and diminishing sensitivity for gains and losses.

As a test of the fit of the parametric model, we compared its predicted equi-probability curves to those of the data, estimated using a semi-parametric local logit estimator. Based on this comparison, we concluded that our data do not reject the parametric model.

We estimated the value functions from our parametric model using mixed logit estimation. The results vary somewhat between the five considered data segments, but the overall picture is consistent with prospect theory: In general, the value functions exhibit loss aversion for both travel time and cost (in the time dimension we have loss aversion for the entire range of considered time changes, while in the cost dimension we only have loss aversion for part of the range of considered cost changes), the value function for cost exhibits diminishing sensitivity for both gains and losses, and the value function for time exhibits constant sensitivity for both gains and losses. We found stronger diminishing sensitivity for money than for travel time, consistent with prospect theory as the explanation of the positive relation between the marginal VTT and the size of the time change.

References

Avineri, E., Bovy, P., 2008. Parameter identification of prospect theory model for travel choice analysis. Transportation Research Record 2082, 141–147. [38]

Bierlaire, M., 2003. Biogeme: A free package for the estimation of discrete choice models. Proceedings of the 3rd Swiss Transportation Research Conference. www.strc.ch/Paper/bierlaire.pdf. [46]

Bierlaire, M., 2005. An introduction to biogeme (version 1.4). http://transp-or2.epfl.ch/biogeme/doc/tutorial.pdf. [46]

Burge, P., Rohr, C., Vuk, G., Bates, J., 2004. Review of international experience in VOT study design. European Transport Conference 2004. [38]

Cantillo, V., Heydecker, B., de Dios Ortúzar, J., 2006. A discrete choice model incorporating thresholds for perception in attribute values. Transportation Research Part B 40, 807–825. [37]

De Borger, B., Fosgerau, M., 2008. The trade-off between money and travel time: A test of the theory of reference-dependent preferences. Journal of Urban Economics 64, 101–115. [37, 38, 39, 40, 43, 50, 51, 53]

de Jong, G., Tseng, Y., Kouwenhoven, M., Verhoef, E., Bates, J., 2007. The value of travel time and travel time reliability: Survey design. Final report. Report to The Netherlands Ministry of Transport, Public Works and Water Management. [38]

Doornik, J. A., 2001. Ox: An Object-Oriented Matrix Language. Timberlake Consultants Press London. [45]

Fan, J., Heckman, N. E., Wand, M. P., 1995. Local polynomial kernel regression for generalized linear models and quasi-likelihood functions. Journal of the American Statistical Association 90, 141–150. [39, 45]

Fosgerau, M., 2007. Using nonparametrics to specify a model to measure the value of travel time. Transportation Research, Part A 41, 842–856. [39, 45]

Fosgerau, M., Hjorth, K., Lyk-Jensen, S. V., 2007. The Danish Value of Time Study: Final report. Report for the Danish Ministry of Transport, Danish Transport Research Institute. [37, 38]

Gunn, H., 2001. Spatial and temporal transferability of relationships between travel demand, trip cost and travel time. Transportation Research, Part E 37, 163–189. [37]

Hultkrantz, L., Mortazavi, R., 2001. Anomalies in the value of travel-time changes. Journal of Transport Economics and Policy 35, 285–300. [37]

Kahneman, D., Tversky, A., 1979. Prospect theory: An analysis of decision under risk. Econometrica 47, 263–291. [38, 40]

Mackie, P., Fowkes, A., Wardman, M., Whelan, G., Nellthorp, J., Bates, J., 2003. Values of travel time savings in the UK – Report to Department for Transport. Institute for Transport Studies, University of Leeds, in association with John Bates Services. [37]

Mackie, P., Jara-Díaz, S., Fowkes, A., 2001. The value of travel time savings in evaluation. Transportation Research, Part E 37, 91–106. [37]

Ramjerdi, F., Flügel, S., Samstad, H., Killi, M., 2010. Den norske verdsettingsstudien, Tid. Report for the Norwegian Ministry of Transport, Institute of Transport Economics, Oslo, Report no. 1053B/2010. [38, 43]

Samstad, H., Ramjerdi, F., Veisten, K., Navrud, S., Magnussen, K., Flügel, S., Killi, M., Halse, A. H., Elvik, R., Martin, O. S., 2010. Den norske verdsettingsstudien, Sammendragsrapport. Report for the Norwegian Ministry of Transport, Institute of Transport Economics, Oslo, Report no. 1053/2010. [43]

Stott, H., 2006. Cumulative prospect theory's functional menagerie. Journal of Risk and Uncertainty 32, 101–130. [40]

Train, K., 2003. Discrete Choice Methods with Simulation. Cambridge University Press, http://elsa.berkeley.edu/books/choice2.html. [46]

Tversky, A., Kahneman, D., 1991. Loss aversion in riskless choice: A reference-dependent model. The Quarterly Journal of Economics 106 (4), 1039–1061. [38]

Van de Kaa, E., 2005. Heuristic judgment, prospect theory and stated preference surveys aimed to elicit the value of travel time. European Transport Conference 2005. [38]

Van de Kaa, E., 2008. Extended prospect theory – findings on choice behaviour from economics and the behavioural sciences and their relevance for travel behaviour. Doctoral thesis, TU Delft. [38]

Wakker, P., 2010. Prospect theory for risk and ambiguity. Cambridge University Press. [40]

Appendix

Table 3.8: Summary statistics of the sample applied in the parametric analysis (trimmed at the 5% and 95% quantiles of Δt and Δc)

	Car short	PT short	Car long	PT long	Air
Sample size					
- individuals	3016	547	1128	939	756
- obs	23892	4375	8514	7023	5739
Reference travel time, t_0					
- min	10.0	10.0	60.0	60.0	80.0
- mean	23.4	27.3	164.8	237.0	181.2
- max	90.0	90.0	645.0	900.0	600.0
Reference cost, c_0					
- min	8.0	10.0	70.0	50.0	150.0
- mean	42.1	30.8	393.5	283.4	1144.3
- max	250.0	100.0	1464.0	1500.0	5000.0
Time attributes, t_j					
- min	-23.0	-25.0	-169.0	-210.0	-143.0
- mean	0.0	0.0	0.2	-0.2	-0.2
- max	24.0	26.0	152.0	252.0	142.0
Time attributes, t_j (gains)					
- min	-23.0	-25.0	-169.0	-210.0	-143.0
- mean	-4.8	-5.6	-33.6	-48.9	-37.6
- max	-1.0	-1.0	-9.0	-9.0	-12.0
Time attributes, t_j (losses)					
- min	2.0	2.0	9.0	9.0	12.0
- mean	4.8	5.6	34.3	47.9	37.3
- max	24.0	26.0	152.0	252.0	142.0
Cost attributes, c_j					
- min	-41.0	-30.0	-455.0	-375.0	-605.0
- mean	0.1	0.3	4.9	4.3	1.7
- max	41.0	31.0	463.0	377.0	604.0
Cost attributes, c_j (gains)					
- min	-41.0	-30.0	-455.0	-375.0	-605.0
- mean	-9.0	-8.5	-119.9	-98.2	-196.0
- max	-1.0	-1.0	-11.0	-11.0	-33.0
Cost attributes, c_j (losses)					
- min	1.0	1.0	11.0	11.0	33.0
- mean	9.8	10.4	146.5	121.6	209.7
- max	41.0	31.0	463.0	377.0	604.0
Choice variable (y)					
- min	0.0	0.0	0.0	0.0	0.0
- mean	0.7	0.7	0.6	0.6	0.7
- max	1.0	1.0	1.0	1.0	1.0

Table 3.9: Estimation Summary – Logit models (MNL1). Parameter estimates with robust standard errors in parentheses.

	Car short	PT short	Car long	PT long	Air
mean ($\log w$)	-0.55^*	-0.65^*	-0.20	-0.11	0.17
	(0.02)	(0.08)	(0.11)	(0.10)	(0.17)
β_c	0.24^*	0.00	0.19^*	0.10^*	0.16^*
	(0.02)	(0.09)	(0.04)	(0.04)	(0.05)
β_t	-0.03	-0.14	-0.03	-0.04	-0.04
	(0.02)	(0.08)	(0.04)	(0.04)	(0.05)
η_c	0.05^*	0.15^*	0.10^*	0.09^*	-0.02
	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)
η_t	0.05^*	0.05	0.10^*	0.05^*	0.03
	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)
μ	1.88^*	1.58^*	1.81^*	1.91^*	1.90^*
	(0.06)	(0.14)	(0.09)	(0.10)	(0.12)
Log likelihood value	-11867.5	-2034.9	-4347.3	-3585.9	-2965.3
Number of est. parameters	6	6	6	6	6
Number of obs.	23892	4375	8514	7023	5739

* denotes significance at the 5% level.

Table 3.10: Estimation Summary – Logit models (MNL2). Parameter estimates with robust standard errors in parentheses.

	Car short	PT short	Car long	PT long	Air
mean ($\log w$)	-0.55^*	-0.64^*	-0.17	-0.11	0.17
	(0.02)	(0.08)	(0.11)	(0.10)	(0.17)
β_c	0.24^*	-0.01	0.18^*	0.10^*	0.16^*
	(0.02)	(0.09)	(0.04)	(0.04)	(0.05)
β_t	-0.03	-0.14	-0.04	-0.05	-0.04
	(0.02)	(0.08)	(0.04)	(0.04)	(0.05)
η_c	0.01	0.02	-0.21^*	-0.27^*	-0.01
	(0.02)	(0.05)	(0.08)	(0.09)	(0.12)
η_t	0.08^*	0.10	0.05	-0.01	0.14
	(0.02)	(0.07)	(0.09)	(0.09)	(0.12)
γ_c	0.02^*	0.08^*	0.07^*	0.08^*	0.00
	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)
γ_t	-0.02	-0.03	0.02	0.02	-0.03
	(0.01)	(0.04)	(0.03)	(0.02)	(0.03)
μ	1.87^*	1.57^*	1.79^*	1.88^*	1.90^*
	(0.06)	(0.14)	(0.09)	(0.10)	(0.12)
Log likelihood value	-11863.4	-2030.4	-4339.1	-3576.9	-2964.8
Number of est. parameters	8	8	8	8	8
Number of obs.	23892	4375	8514	7023	5739

* denotes significance at the 5% level.

Table 3.11: Likelihood ratio tests (p-values)

Hypothesis	p-values				
	Car short	PT short	Car long	PT long	Air
v_t linear for gains: $\beta_t = -\gamma_t$	0.19	< 0.01	0.84	0.78	0.16
v_t linear for losses: $\beta_t = \gamma_t$	0.81	0.10	0.21	0.05	0.18
v_t piecewise linear: $\beta_t = \gamma_t = 0$	0.40	0.02	0.43	0.10	0.22
v_c linear for gains: $\beta_c = -\gamma_c$	< 0.01	0.30	< 0.01	< 0.01	0.01
v_c linear for losses: $\beta_c = \gamma_c$	< 0.01	0.73	< 0.01	0.03	0.01
v_c piecewise linear: $\beta_c = \gamma_c = 0$	< 0.01	0.07	< 0.01	< 0.01	0.02
v_t and v_c piecewise linear: $\beta_t = \gamma_t = \beta_c = \gamma_c = 0$	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
No gain-loss asymmetry for time: $\eta_t = \gamma_t = 0$	< 0.01	0.01	< 0.01	< 0.01	0.06
No gain-loss asymmetry for cost: $\eta_c = \gamma_c = 0$	< 0.01	< 0.01	< 0.01	< 0.01	0.85
No gain-loss asymmetry: $\eta_t = \gamma_t = \eta_c = \gamma_c = 0$	< 0.01	< 0.01	< 0.01	< 0.01	0.18

Note: The piecewiese linear formulations have separate slopes for gains and losses.

Chapter 4

Loss aversion and individual characteristics

Loss aversion and individual characteristics

Katrine Hjorth and Mogens Fosgerau
Accepted for publication in *Environmental and Resource Economics*.[1]

Abstract

Many studies have shown that loss aversion affects the valuation of non-market goods. Using stated preference data, this paper presents an empirical investigation of how individual-level loss aversion varies with observable personal characteristics and with the choice context. We investigate loss aversion with respect to travel time and money, and find significant loss aversion in both dimensions. The degree of loss aversion in the time dimension is larger than in the money dimension, and depends on age and education. Subjects tend to be more loss averse when the reference is well established.

4.1 Introduction

Employing stated preference data where subjects trade travel time for travel cost, this paper investigates how loss aversion in the time and cost dimensions varies with individual characteristics and features of the experimental design.

The term loss aversion denotes the well-known phenomenon that people are significantly more averse to losses relative to some reference point, than they are attracted to same-sized gains. Loss aversion leads to a gap between willingness-to-accept (WTA) and willingness-to-pay (WTP). The more loss aversion in either dimension, the larger is the WTA-WTP gap. The gap has been studied extensively and has been shown to be strongly present for a wide range of goods, both in hypothetical stated preference experiments, and in field and laboratory experiments (Horowitz and McConnell, 2002; Sayman and Öncüler, 2005).

The WTA-WTP gap is hard to reconcile with Hicksian preferences[2]: Using laboratory experiments involving Coke and luxury chocolates, Bateman et al. (1997) have presented evidence that the gap remains when controlling for income and substitution effects, in contradiction of conventional theory. More generally, the size of the gap is so large that it is unlikely to be entirely due to income effects (Horowitz and McConnell, 2003). The gap therefore poses a serious problem for economic valuation of non-market goods: On one hand, it appears to be a robust phenomenon of economic significance. On the other hand, given that reference points may be labile, in the sense that people quickly adapt to their new reference points after a change, it is debatable

[1] Vol. 49(4), 2011; doi: 10.1007/s10640-010-9455-5. This version is a slightly revised version of the journal version: Notation has been adapted to the style of the thesis.

[2] We adopt the term ”Hicksian preferences” from Bateman et al. (1997), meaning the preference structure usually assumed in conventional neoclassical theory of consumer choice.

whether the application of reference-dependent measures as WTP and WTA in evaluation is meaningful in anything but the very short run.[3] This is particularly relevant for transport infrastructure investments (our application) and many environmental policies, as they often have long-term implications. As long as evaluation is based on measured preferences subject to reference-dependence, it is therefore highly important to understand how loss aversion arises in the experiments that are used to measure preferences, and how the degree of loss aversion varies between different experimental setups and population groups.

Several studies have investigated the extent of heterogeneity in loss aversion or the WTA-WTP gap, either by measuring at the individual level or by comparing averages over groups of subjects. Roughly, the studies can be divided into two categories: One works with preferences for money, generally measured from laboratory experiments with choices/auctions involving lotteries, and often for samples of college students (Loomes et al., 2003, 2010; Harrison and Rutström, 2008, 2009; Schmidt and Traub, 2002; Brooks and Zank, 2005; Booij and van de Kuilen, 2009). The other category works in a two-good scenario, most often money and a non-monetary good, and measures trade-offs between the two goods (Johnson et al., 2006; Gächter et al., 2007; List, 2005, 2007; Plott and Zeiler, 2005). To our knowledge, none of the latter studies measures loss aversion separately in the money dimension and the good dimension, as can be done by considering both gains and losses in both dimensions, see e.g. Bateman et al. (1997).[4] Instead they measure only WTA and WTP, and analyse heterogeneity in the WTA-WTP gap.[5]

The current paper estimates loss aversion at the individual level and separately in the time and money dimensions. In this way we are able to provide new evidence on factors that determine the degree of loss aversion. In particular, we are able to examine how loss aversion in time and money correlates with gender, age, income etc. as well as with aspects of the choice context. Our econometric analysis is facilitated by the use of a large panel data set with more than 1,600 individuals. The panel nature of the data allows us to identify the parameters of interest under weak assumptions, while the size of the data set allows us to estimate the effect of many exogenous characteristics.

We find that the degree of loss aversion in the travel time dimension is larger than in the cost dimension, and increases with age and decreases with the level of education. Further, our results suggest that people tend to be more loss averse when the reference

[3]Following Köszegi and Rabin (2004, 2006)'s line of reasoning – that reference points are likely to depend on subjects' expectations and not just on their status quo situation – reference points are inherently labile. Moreover, as noted by Loomes et al. (2010), there is considerable experimental evidence that points in this direction, for example from laboratory experiments, where subjects adapt instantly to new reference points and exhibit loss aversion about giving up trivial quantities of consumer goods, such as a coffee mug or a chocolate bar, that they have received only a few minutes before (see, e.g., Kahneman et al., 1990). In a (hypothetical) financial framework, Arkes et al. (2008) have specifically tested how subjects adapt their reference after a change, and found that reference points were adapted instantly upwards after gains and downwards after losses, but that the degree of adaptation was larger following gains than following losses.

[4]See Bateman et al. (2005) for a discussion of loss aversion in the money dimension.

[5]Instead of WTP, Johnson et al. (2006) use a so-called "choice valuation", which is similar, except that no reference is specified.

is well established: Subjects exhibit less loss aversion in an experiment, where the reference point has a more hypothetical nature, and particularly if they are unfamiliar with this reference point.

The paper is organised as follows. Section 4.2 reviews the empirical evidence regarding heterogeneity in loss aversion. Section 4.3 formulates our econometric model, and section 4.4 presents the empirical analysis. Section 4.5 concludes.

4.2 Background: The empirical evidence

4.2.1 Variation in individual-level loss aversion or WTA-WTP gap

This section reviews the studies that investigate the variation in individual-level loss aversion or WTA-WTP gap with socio-economic characteristics. Harrison and Rutström (2008) fit a cumulative prospect theory (CPT) model to lottery data, and parameterise the loss aversion parameter as a function of age, gender, race, and grade point average. None of these variables turn out to have a significant effect on the degree of loss aversion. A slightly different analysis (Harrison and Rutström, 2009), using a behavioural model that is a mixture between expected utility theory and CPT, shows similar results, only here race turns out to be significant.

Schmidt and Traub (2002) and Brooks and Zank (2005) do not make assumptions about the functional form of the utility function, but investigate choices between lotteries with constant expected value and equal probability of gaining or loosing a variable amount x. Individuals who systematically favour the lottery with the smaller value of x are interpreted as loss averse. Both studies find that women are significantly more loss averse than men.

Johnson et al. (2006) analyse variation in individual-level loss aversion for four attributes of a car choice experiment. They define loss aversion for an attribute as the ratio between the WTA valuation, where subjects are asked to imagine a certain reference level of the attribute, and the so-called "choice valuation", which is similar, except that no reference is mentioned. Gächter et al. (2007) investigate the individual-level WTA-WTP gap for valuations of a toy car. Both studies find that loss aversion, in the form of the gap between valuation measures, increases with age and income, while there is no significant effect of gender. Johnson et al. (2006) report that unemployed, students, people working at home, workers, and farmers appear to be more loss averse than managers and entrepreneurs, but that the difference is only marginally significant, once other covariates are controlled for.[6] Gächter et al. (2007) report that loss aversion decreases with the level of education, while this effect is not significant in Johnson et al. (2006), once other covariates are controlled for. Johnson et al. (2006) also document an effect of market experience: The gap is smaller for subjects who have specific knowledge about the attribute or have experience with the considered class of cars.

Booij and van de Kuilen (2009) use a lottery experiment to measure loss aversion for subjects in a representative Dutch household panel. The degree of loss aversion is

[6] Gächter et al. (2007) find a similar occupational pattern, but it is not clear whether the effect remains after controlling for other covariates.

defined as the ratio between the steepness of the utility function for gains and for losses for specified intervals of gains and losses. They find significant effects of gender and education, with women being more loss averse than men, and highly educated people being less loss averse then others. Age and income do not have a significant effect.

4.2.2 Between-group variation in average/median WTA-WTP gap

In addition to the literature investigating variation with individual characteristics, various studies have investigated how the gap between WTA and WTP, measured as averages or medians over groups of subjects, is affected by learning and market experience, and by experimental design features such as incentive structure and elicitation method.

Loomes et al. (2003, 2010) measure the WTA-WTP gap for lotteries, and find that market interaction tends to reduce the gap, both through shaping (that valuations are affected/shaped by observing other people's market behaviour) and through market discipline (subjects adjust behaviour if the market punishes their errors). List (2005, 2007), in a field experiment measuring the WTA-WTP gap for sports memorabilia, finds that the gap is smaller for subjects who have experience with trading the good, or with trading in general.

Plott and Zeiler (2005) suggest that the WTA-WTP disparity observed in experiments may be due to subjects' misconceptions. Using laboratory experiments measuring WTA and WTP for mugs, they find no significant WTA-WTP gap in an experiment thoroughly explaining subjects the incentive-compatible elicitation mechanism, while they find a significant WTA-WTP gap in an experiment, which does not contain such information. However, Plott and Zeiler (2005)'s misconception hypothesis is disputed by Isoni et al. (2011): Using another set of Plott and Zeiler (2005)'s experiments, measuring WTA and WTP for lotteries over money, they show that the WTA-WTP gap persists when subjects are informed about the elicitation mechanism. They replicate the results in a new set of experiments, showing that the WTA-WTP gap persists in experiments with lotteries over money, while it disappears in experiments with mugs and lotteries over chocolate.

Two meta-studies by Horowitz and McConnell (2002) and Sayman and Öncüler (2005) shed further light on the relation between the WTA-WTP gap and experimental design: Horowitz and McConnell (2002) find that experiments with real pay-offs do not yield WTA-WTP ratios that are significantly different from those of hypothetical experiments, and that studies that are incentive-compatible have significantly larger WTA-WTP gaps. Sayman and Öncüler (2005), on the other hand, report that incentive-compatible experiments tend to yield smaller gaps. They also find an effect of experience, as studies with "practice rounds" yield smaller WTA-WTP gaps. Both studies make the interesting observation, that the WTA-WTP gap is larger, the farther a good is from being an ordinary private good.

4.3 Model formulation

Our starting point is a framework that defines the relation between loss aversion relative to a reference point r, underlying reference-free utility u, and choice utility U. Choice utility rationalises observed behaviour, which may be reference-dependent and exhibit loss aversion. Although the reference point is fixed for any individual in our data, it is useful to include reference-free utility in the framework in order to make it visible how the reference point may affect the observed choices. There are several different approaches to describing the relation between choice utility and underlying reference-free utility, e.g. Munro and Sugden (2003), Köbberling and Wakker (2005), Köszegi and Rabin (2006), De Borger and Fosgerau (2008), and Fosgerau and De Borger (2009). These papers define reference-free preferences as a normative concept based on neoclassical theory, and indicate how these preferences may be recovered from observed choices subject to loss aversion.[7]

Neither reference-free utility, loss aversion, nor choice utility are observed, and we consider a situation where we are not able to induce changes to the reference point. Therefore it is necessary to introduce some normalisation assumptions in order to identify loss aversion separately from the curvature of reference-free preferences.[8]

We employ the formulation from Fosgerau and De Borger (2009) with symmetric loss aversion. This formulation is convenient in our econometric model. The model is formulated for two goods, and the choice utility is given by

$$U(x_1,x_2|r) = u(r) + u_1(r)\exp(-\eta_1 S(x_1))x_1 + u_2(r)\exp(-\eta_2 S(x_2))x_2. \tag{4.1}$$

x_1 and x_2 denote changes in the two good dimensions, relative to the reference point r, such that positive values correspond to gains and negative values to losses. $S(\cdot)$ is the sign function, and u_1 and u_2 are the reference-free marginal utilities. With this formulation, the marginal choice utilities in the gain direction equal the reference-free marginal utilities times $\exp(-\eta)$, while in the loss direction they equal the reference-free marginal utilities times $\exp(\eta)$. The parameters η_1 and η_2 thus determine the degrees of loss aversion in the two dimensions. When $\eta_1 = \eta_2 = 0$, there is no loss aversion, and the formulation reduces to a linear approximation to reference-free utility. Note that the reference-free utility at the reference, $u(r)$, plays no role in comparisons involving a fixed reference.

Consider a choice between two travel alternatives (e.g. routes), that are identical except that one alternative is faster and more expensive than the other. In a given choice, label the alternatives 1 and 2, where alternative 1 with travel time and cost (t_1, c_1) is the faster and expensive alternative, and alternative 2 with attributes (t_2, c_2) is the slower and cheaper alternative. Let (t_0, c_0) denote the reference travel time and cost. An underlying assumption of our model is that both travel time and cost are bads, such that utility is non-increasing in both attributes. Hence, a gain corresponds to a travel time (cost) less than the reference, while a loss corresponds to a travel time (cost) larger than the

[7]The papers use a variety of terms for such preferences: Basic, intrinsic, consumption, or hedonic preferences.

[8]See e.g. the comment in Köbberling and Wakker (2005).

reference. Applying this to the model in eq. (4.1), the choice utility of alternative j can be written as

$$(4.2)\qquad \begin{aligned} U(t_j, c_j | t_0, c_0) = u(t_0, c_0) + u_t(t_0, c_0) \exp\left(\eta_t S(t_j - t_0)\right)(t_j - t_0) \\ + u_c(t_0, c_0) \exp\left(\eta_c S(c_j - c_0)\right)(c_j - c_0), \end{aligned}$$

where u_t and u_c are the marginal utilities of travel time and cost, respectively, and are assumed to be negative.

We assume that individuals maximise the choice utility in eq. (4.2). It is straightforward to show that alternative 1 - the faster alternative - has a higher choice utility than alternative 2, whenever

$$(4.3)\qquad \log w + \log \Delta V_t - \log \Delta V_c > 0,$$

where

$$(4.4)\qquad \Delta V_t := \exp\left(\eta_t S(t_2 - t_0)\right)(t_2 - t_0) - \exp\left(\eta_t S(t_1 - t_0)\right)(t_1 - t_0),$$

$$(4.5)\qquad \Delta V_c := \exp\left(\eta_c S(c_1 - c_0)\right)(c_1 - c_0) - \exp\left(\eta_c S(c_2 - c_0)\right)(c_2 - c_0),$$

and $w = \frac{u_t}{u_c}$ is the marginal rate of substitution (MRS) between travel time and cost. The MRS may be any function of individual characteristics, the reference point, and the choice situation. Note that ΔV_t and ΔV_c are positive, regardless of the sign of η_t and η_c, since $t_1 < t_2$ and $c_1 > c_2$.

A higher degree of loss aversion in the time dimension, corresponding to a higher value of η_t, makes choosing the faster alternative more likely when comparing the reference travel time to a time loss ($t_1 = t_0 < t_2$), and less likely when comparing the reference travel time to a time gain ($t_1 < t_0 = t_2$). A higher value of η_c makes choosing the faster alternative less likely when comparing the reference cost to a money loss ($c_1 > c_0 = c_2$), and more likely when comparing the reference cost to a gain ($c_1 = c_0 > c_2$).

To formulate our econometric model, it is convenient to index variables according to individual i and choice situation s. Let y_{is} be 1 when individual i chooses the faster and more expensive alternative in choice s, and 0 otherwise. We apply a stochastic discrete choice model, in which people do not deviate systematically from the rule in eq. (4.3): We assume that

$$(4.6)\qquad y_{is} = 1 \iff \log w_{is} + \log \Delta V_{t,is} - \log \Delta V_{c,is} > \frac{\varepsilon_{is}}{\mu},$$

where ε_{is} is a standardised and symmetric random error term with mean zero, and μ is a scale parameter. The error term represents computational and judgmental errors made by the decision maker, as well as measurement and specification errors. The error terms are assumed to be independent and identically distributed across all choices (also choices of the same individual), such that any systematic tendency within the individual is captured by w. This implies that $y_{i1} \ldots y_{iS}$ are independent conditional on $\{w_{is}, \eta_{t,is}, \eta_{c,is}, t_{k,is}, c_{k,is} | s = 1 \ldots S, k = 0, 1, 2\}$.

We allow for heterogeneity in loss aversion by letting the degrees of loss aversion vary with characteristics of the individual and the situation. As we do not wish to restrict the sign of the η's, we assume they are linear functions of the parameters:

$$\eta_{t,is} = \gamma_t{}' z_{t,is} \tag{4.7}$$

$$\eta_{c,is} = \gamma_c{}' z_{c,is} \tag{4.8}$$

where γ_t, γ_c are parameter vectors, and $z_{t,is}$ and $z_{c,is}$ are vectors of covariates related to the individual and the choice situation. Both covariate vectors contain a constant.

Based on Fosgerau (2007), the log MRS is parameterised as:

$$\log w_{is} = \beta' x_{is} + \zeta_i \tag{4.9}$$

where β is a parameter vector, x_{is} is a vector of covariates related to the individual and the choice situation, and ζ_i is an individual-specific random term that represents unobserved heterogeneity.

4.4 Empirical analysis

4.4.1 Data

Our data are from a survey conducted to establish the marginal value of travel time to be used in welfare-economic evaluations of transport infrastructure policies (Fosgerau et al., 2007). We use two stated preference experiments, where subjects make trade-offs between travel time and travel cost by choosing either a fast and expensive trip or a slower and cheaper one. As is typical for survey data, all choices are hypothetical.

Interview procedure

Subjects were sampled from Gallup's Danish Internet and Phone panels or contacted at educational institutions.[9] Subjects in the Internet panel were asked to complete the questionnaire on-line themselves, while the remaining subjects were interviewed face-to-face, using the same questionnaire on a laptop.

In the beginning of each interview, the subject was asked to state the types of trips he had made within the last eight days, distributed on travel mode, trip length, and trip purpose.[10] One of these trips was selected at random as base of the first experiment; we label this the *real base trip*. In our analysis we use data for car trips only.

Subjects were interviewed in detail about the real base trip, giving information such as the travel time, cost, number of accompanying persons, day of travel, congestion, delays, how often the trip was made, if they had to arrive at a fixed time or had some

[9]The Internet panel is representative of the Danish population aged 15-59 with Internet access. The Phone panel, which is representative of the entire Danish population, was used to sample individuals from socio-economic groups that are poorly represented in the Internet panel, e.g. older people. To fulfil sampling quotas on trip purpose, additional interviews were carried out at educational institutions. As a consequence, the sample is not representative of the Danish population in general, nor of the population of travellers. In terms of age, the young and older generations are overrepresented; in terms of occupation, students and retired are overrepresented, while wage earners are underrepresented.

[10]International trips, business trips, and trips shorter than five minutes were not included.

Table 4.1: Choice types

	Fast alternative		Slow alternative	
Choice type	Travel time	Travel cost	Travel time	Travel cost
WTP	$t_0 - \Delta t$	$c_0 + \Delta c$	t_0	c_0
WTA	t_0	c_0	$t_0 + \Delta t$	$c_0 - \Delta c$
EL	t_0	$c_0 + \Delta c$	$t_0 + \Delta t$	c_0
EG	$t_0 - \Delta t$	c_0	t_0	$c_0 - \Delta c$

Note: $\Delta t > 0$ and $\Delta c > 0$ denote the difference in travel time and cost, respectively, between the two alternatives.

flexibility, etc. The cost of the real base trip encompassed direct driving costs (i.e. not taxes and maintenance costs), parking costs, and bridge tolls. The direct driving cost was computed by multiplying the trip length by a fixed kilometre cost of 0.75 DKK.[11] Subjects were asked if this amount was acceptable, and if not they were asked to state the amount they perceived to be the correct driving cost, and this measure was used instead.

Subjects then participated in the first stated preference experiment (SP1), where they had to make choices between variations of the real base trip. This is described in detail in the section below. After this experiment, subjects were asked to state which transport mode they would use instead, if the car mode was unavailable; the trip with this alternative transport mode is labelled the *alternative base trip*. Subjects stated the travel time and cost of the alternative base trip, and indicated how often they made the alternative base trip, and how often they used the alternative mode in general. They then participated in the second experiment (SP2), where they had to make choices between variations of the alternative base trip. Only subjects who had an alternative transport mode, and had used this mode for some type of trip within the last year, participated in SP2. Finally, subjects answered a series of background questions regarding their socio-economic characteristics.

Stated preference experiments

Each experiment consisted of eight binary choices between travel alternatives described by in-vehicle travel time and travel cost, where one alternative was faster and more expensive than the other. The order of the alternatives on the screen (left/right) was random. SP1 also contained a check question, where one alternative was faster and cheaper than the other.

Experiments were framed relative to a base trip; in SP1 this was the real base trip, while in SP2 it was the alternative base trip. Subjects were instructed to pretend they were to make the base trip again, but now facing different travel times and costs. It was stressed that in every other aspect - such as transport mode, trip purpose, and time constraints at the origin and destination, the travel alternatives were exactly as the base

[11] 1 Euro $\approx$ 7.5 DKK.

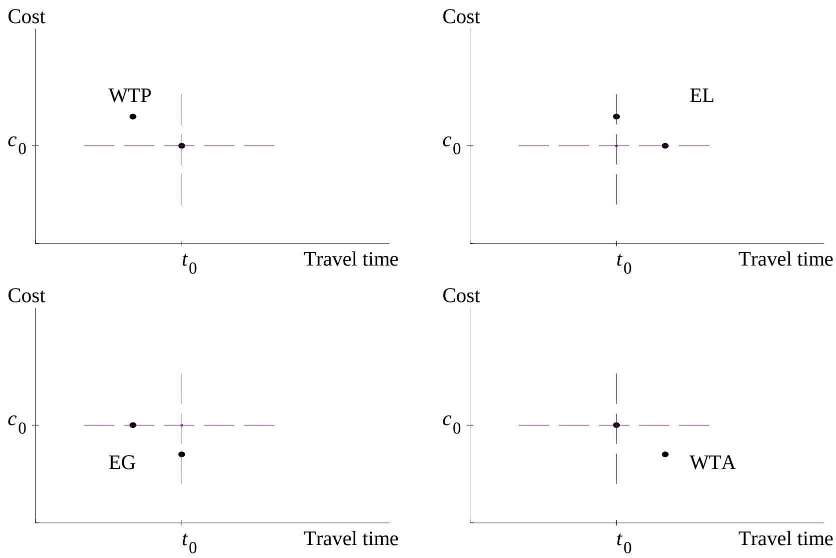

Figure 4.1: Choice types. Alternatives are denoted by dots. The intersection of the dashed lines is the reference (t_0,c_0).

trip. Because of this emphasis on the base trip and the alternative base trip as the ”normal” situation, it seems fair to assume that these trips serve as a reference for preference formation, despite the potential problem that the base trip might not correspond to the subject’s idea of ”normal”, if e.g. the base trip happened to be extraordinarily delayed. In a given experiment, we therefore consider the travel time and cost of the experiment’s base trip, denoted t_0 and c_0, to be the subject’s reference levels of travel time and travel cost.

Choice situations were generated by varying time and cost around (t_0, c_0). All subjects were presented with both gains (decreases) and losses (increases) in both attributes, defining four types of choices. We adopt the terminology from De Borger and Fosgerau (2008), and refer to the choice types as WTP, WTA, equivalent loss (EL), and equivalent gain (EG). The types are defined in Table 4.1: WTP choices compare the base trip to a time decrease/cost increase, WTA choices compare the base trip to a time increase/cost decrease, EL choices compare a time increase to a cost increase, and EG choices compare a time decrease to a cost decrease.[12] The choice types correspond to the quadrants of the time/cost plane with origin in (t_0,c_0), as shown in Figure 4.1.

There were eight trade-offs in each experiment, two of each choice type. The travel alternatives were generated as follows: First, a time difference $\Delta t > 0$ was drawn randomly from a subset of $\{3, 5, 10, 15, 20, 30, 45, 60\}$ minutes; the subset depending on t_0, such that subjects were only offered meaningful time differences. Then four trade-off prices v were drawn at random from the interval [0.50, 3.33] DKK per minute, and for each trade-off price the cost difference of the alternatives was computed as $\Delta c = v \cdot \Delta t$, rounded to the nearest 0.50 DKK. Finally, the four pairs (Δt,Δc) were assigned randomly to the four quadrants, with one pair in each quadrant. The process was repeated

[12]Note that our definition does not correspond exactly to Bateman et al. (1997)’s definition of valuation measures, as we keep the reference point fixed.

to generate another four choices, and the eight choices were presented to the subject in random sequence.

The values presented on the screen were absolute levels of travel time and cost, rather than changes from the base trip. In SP1, where the base trip was a car trip, subjects were supposed to pretend that the relative level of congestion was the same as for the base trip. Rather than stating this instruction, the extent of congestion in a given alternative was made explicit by decomposing the travel time attribute into free-flow time (travel time with no other cars on the road) and additional time due to congestion, with the ratio of the two kept fixed, and equal to that of the base trip, throughout the experiment.

For subjects with a short base trip ($t_0 \leq 10$ minutes), choice situations were generated by varying time and cost around (t_0+2, c_0), such that the time attribute could still be varied both up and down.

Sample selection

We use data where the real base trip is a car trip with the subject as driver, and the alternative transport mode is bus or train, or the subject does not have an alternative mode. Excluding private trips paid by the employer, this provides us with a sample of 2582 individuals. To mitigate possible bias arising from subjects' misunderstanding, we exclude individuals who chose the dominated alternative in the check question (15% of the sample), and individuals stating unrealistic values of, e.g., speed, cost, and travel time of their base trip (10% of the sample). Further, we exclude observations where $\Delta c = 0$ due to rounding. The final data set contains 2001 individuals and 18,814 observations; 15,488 in SP1, and 3326 in SP2.

Note that lexicographic choosers (subjects who consistently chose either the faster alternative or the cheaper alternative) do not contribute to identification of the degree of loss aversion: Loss aversion in the time dimension is identified by observing the cheaper alternative being chosen in a WTP (EG) choice, while the fast alternative is chosen in an EL (WTA) choice with a trade-off price at least as large. In the cost dimension loss aversion is identified by similarly comparing EG (WTA) to WTP (EL) choices. The effective sample size therefore reduces to 1606 individuals and 14,813 observations.

4.4.2 Loss aversion in the raw data

Before estimating our discrete choice model, we compare the data to the predictions of the theoretical model in eq. (4.3). In the case with no gain-loss asymmetry ($\eta_t = \eta_c = 0$), eq. (4.3) reduces to $w > v$, where $v = \frac{\Delta c}{\Delta t}$ is the trade-off price of time in the choice. So with no gain-loss asymmetry, the theoretical model predicts that subjects will choose the faster alternative whenever $w > v$. As mentioned above, a higher degree of loss aversion in the time dimension will affect the likelihood of choosing the faster alternative in opposite directions, depending on whether the choice represents a time gain or a time loss. The same holds in the cost dimension. We therefore inspect how often the faster alternative is chosen as a function of v, depending on whether the choice represents a gain or a loss in the time and cost dimensions.

Figure 4.2 plots the share of observations where the cheaper alternative is chosen as a function of v, separately for time losses and time savings, while Figure 4.3 shows the same for cost increases and cost savings. Data are smoothed using a non-parametric Gaussian kernel estimator (Li and Racine, 2007). From both Figures it is evident that the share of subjects who opt for the cheaper alternative increases as v increases.

Looking at Figure 4.2, we see that people are less likely to choose the cheaper alternative if they are faced by a time loss than if they are faced by a time saving. This indicates that the unit value assigned by an individual to a time loss exceeds the unit value assigned to a time saving. Similarly, we see in Figure 4.3 that people are more likely to choose the cheaper alternative if faced by a cost increase than if they are faced by a cost saving, indicating that the unit value of a cost increase exceeds the unit value of a cost saving.

Hence, from the raw data it is evident that losses are valued at higher unit values than gains. We cannot tell how much of the difference that is caused by loss aversion, because we do not control for preference curvature, but the difference seems substantial.

4.4.3 Model specification

Fixed effects logit estimator

In this section we discuss how we estimate the parameters of interest, γ_t and γ_c. For notational convenience, we define

$$
\begin{aligned}
t_{is} &:= (t_{1,is} - t_{0,is}) + (t_{2,is} - t_{0,is}),\\
c_{is} &:= (c_{1,is} - c_{0,is}) + (c_{2,is} - c_{0,is}).
\end{aligned}
$$

Due to the experimental design of our data, the choice model in eq. (4.6) can be rewritten as follows below, using the parameterisations in equations (4.7), (4.8), and (4.9). Details are given in the Appendix. Recall that the experimental design for subjects with a reference travel time of more than 10 minutes differs from the design for subjects with a shorter reference time. For subjects with a reference travel time of more than 10 minutes ($t_0 > 10$), we get

$$
\begin{aligned}
& y_{is} = 1 \\
& \Updownarrow \\
& \beta' x_{is} + \zeta_i + \gamma_t' z_{t,is} S(t_{is}) + \log|t_{is}| - \gamma_c' z_{c,is} S(c_{is}) - \log|c_{is}| > \frac{\varepsilon_{is}}{\mu}.
\end{aligned} \tag{4.10}
$$

For subjects with a reference travel time less than or equal to 10 minutes ($t_0 \leq 10$), we get for WTP and EG choices that

$$
\begin{aligned}
& y_{is} = 1 \\
& \Updownarrow \\
& \beta' x_{is} + \zeta_i + \log(2\exp(\gamma_t' z_{t,is}) + \exp(-\gamma_t' z_{t,is})|t_{1,is} - t_{0,is}|) - \gamma_c' z_{c,is} S(c_{is}) - \log|c_{is}| > \frac{\varepsilon_{is}}{\mu},
\end{aligned} \tag{4.11}
$$

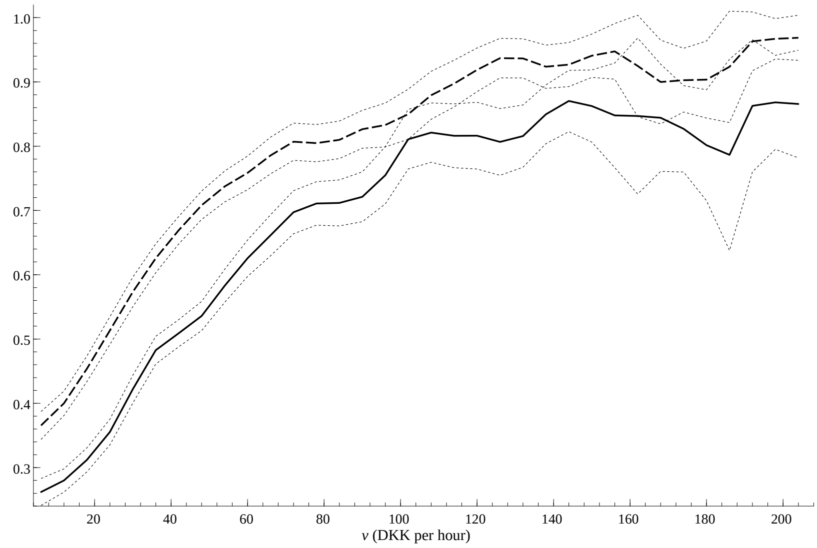

Figure 4.2: Share of observations choosing cheaper alternative as a function of $v = \Delta c/\Delta t$ for time losses (solid curve) and time savings (dashed curve), with confidence limits (dotted curves). Note that the confidence limits do not take into account the panel structure of the data; hence precision is overestimated.

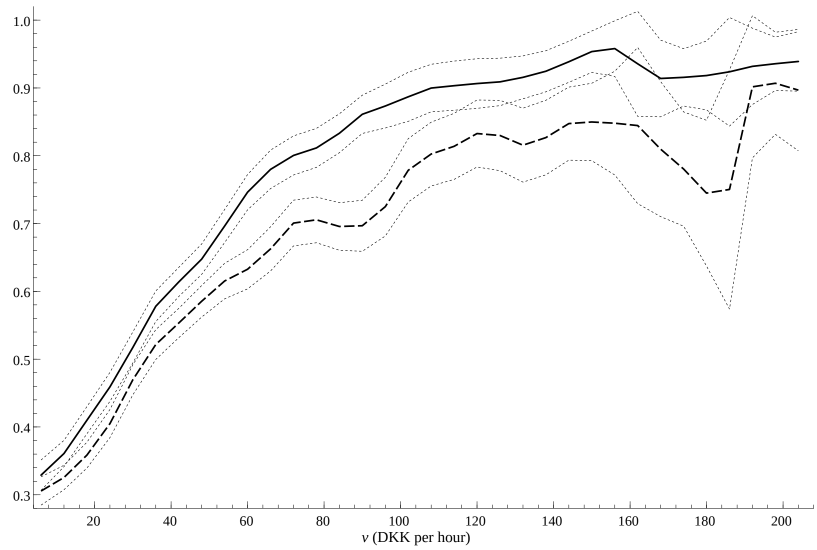

Figure 4.3: Share of observations choosing cheaper alternative as a function of $v = \Delta c/\Delta t$ for cost increases (solid curve) and cost savings (dashed curve), with confidence limits (dotted curves). Note that the confidence limits do not take into account the panel structure of the data; hence precision is overestimated.

and for WTA and EL choices that

$$
\text{(4.12)} \quad
\begin{aligned}
& y_{is} = 1 \\
& \Updownarrow \\
& \beta' x_{is} + \zeta_i + \gamma_t{}' z_{t,is} + \log(t_{2,is} - t_{0,is} - 2) - \gamma_c{}' z_{c,is} S(c_{is}) - \log|c_{is}| > \frac{\varepsilon_{is}}{\mu}.
\end{aligned}
$$

We assume that the errors (ε_{is}) are iid logistic random variables with standard deviation $\frac{\pi}{\sqrt{3}}$, and we allow for different effects of unobserved heterogeneity in the two experiments by assuming that there are two (potentially correlated) individual-specific effects, ζ_i^{SP1} and ζ_i^{SP2}.

For robustness, we apply the fixed effects logit estimator from Chamberlain (1984), where the likelihood contribution of individual i is the probability of choosing the sequence $(y_{i1}...y_{iS})$, conditional on the covariates and on the number of times the fast alternative is chosen in each experiment. Since the contribution of the unobserved effect (ζ_i^{SP1} or ζ_i^{SP2}) to the choice rules above is additive, and is constant within the individual and experiment, the unobserved effect cancels out of the likelihood function of the fixed effects logit estimator. Similarly, any factor in x_{is} that is invariant within the individual and experiment, cancels out of the likelihood function. This means that we only identify the β's which correspond to covariates in x_{is} that vary within the individual. The parameters of interest, γ_t and γ_c, are identified, because the contributions of $z_{t,is}$ and $z_{c,is}$ vary across choice types.

The great advantage from using this approach is that because the unobserved effects ζ_i^{SP1} and ζ_i^{SP2} cancel out of the likelihood function, we do not have to impose any assumption on their distribution and their correlation with each other and with x_{is}. Whereas the often applied random effects estimator that integrates out the ζ_i's relies on the strong assumption of independence between the ζ_i's and x_{is} to be consistent, the fixed effects logit estimator is consistent and asymptotically normal, as long as $y_{i1} \dots y_{iS}$ are independent conditional on $\{\zeta_i^{SP1}, \zeta_i^{SP2}, x_{is}, z_{t,is}, z_{c,is} | s = 1 \dots S\}$.

Moreover, we do not have to specify how the log MRS depends on the reference travel time and cost (t_0 and c_0), as long as their effect on the log MRS is additively separable from the effect of characteristics that vary within the individual and experiment. In this case, the effect of t_0 and c_0 cancels out of the likelihood function, and the estimator is consistent without any other assumptions regarding the functional form of the effect. In particular, the estimator is robust with regards to preference curvature, if this curvature is captured by t_0 and c_0.

In many applications, the fixed effects logit estimator is disadvantaged, because it does not identify the effect of person-invariant characteristics on choice probabilities (see e.g. Wooldridge, 2002). In our case, we are unable to calculate the MRS, since it depends on the unobserved effect and - in an unidentifiable way - on person-invariant characteristics. However, this is of little importance in our application, since we are only interested in the level of loss aversion, and identification of the factors that determine it, and not in the MRS and the choice probabilities. Since γ_t and γ_c are identified, we are able to calculate the degree of loss aversion for a given individual as well as for a representative individual with certain levels of covariates.

Naturally, the advantages of the fixed effects estimator come with a cost in terms of efficiency, as the estimator will have a larger variance than a correctly specified random effects estimator, because the method does not use information from interpersonal variation.

Covariates

Table 4.2 in the Appendix lists summary statistics of the variables used in the analysis.

The evidence from the reviewed literature suggests to include age, income, education and occupation in z_t and z_c. For a flexible age pattern, we include dummies for age intervals "below 25", "25-34", "35-44", "45-54" and "above 65". To control for occupation, we use dummies for students, retired, and people out of work - the base group being workers and self-employed. Moreover, we include a constant, the demeaned logarithm of personal net income, a dummy for missing income information, a gender dummy, and two education dummies indicating high school and higher education as the latest finished education - with primary/lower secondary school or vocational training as the base group.

In addition to socio-economic characteristics, we add t_0 and c_0 to z_t and z_c to allow the degrees of loss aversion to be affected by the reference point.

We also allow for the familiarity with the reference point to affect the degree of loss aversion. Several factors may affect the familiarity: First, we consider it relevant to distinguish between the two experiments, because *i)* the first experiment concerns a transport mode the subject has shown to prefer to the mode in the second experiment, and *ii)* the reference of the second experiment is of a more hypothetical nature. We therefore include a dummy for the second experiment. Another important indicator of familiarity is how often the subject makes a trip like the base trip or alternative base trip. Trip frequency is a categorical variable with levels "daily" (at least 4-5 times a week), "weekly" (once a week or a couple of times a week), "rarely" (more seldom) and "never".[13] We include dummies for "daily", "weekly" and "never" (base group: "rarely"), and make the dummies experiment-specific to control for interaction between experiment and frequency.

Finally, we include in z_t and z_c a variable measuring the level of congestion on the real base trip.[14] The variable is defined as (t_0 - free flow travel time) / t_0. Since the day-to-day variability of travel times tends to increase with the level of congestion, subjects with congested base trips are likely to have experienced a range of travel times for similar trips, and this may affect their valuation of losses relative to gains.

Regarding the log MRS, the vector x includes $\log\Delta t$, with separate coefficients for time losses and gains, where $\Delta t = (t_2 - t_1)$ is the time difference between the two alternatives. Including $\log\Delta t$ serves to control for preference curvature around the reference point. Most of the explanatory variables often used to explain the MRS, such as income and trip purpose, are invariant across observations from the same individual, and thus

[13] Since the reference in the first experiment is a real trip, frequency cannot be "never" in this experiment.

[14] Congestion is only recorded for car trips, i.e. in experiment 1.

cancel out of the likelihood function. For the same reason, we do not include a constant term.

4.4.4 Results

All estimations are carried out in Ox (Doornik, 2001), and the estimation results are given in Tables 4.3 - 4.4 in the Appendix.

The initial model, Model 1, includes all the covariates mentioned in section 4.4.3. We then reduce the model in three steps. In the first step we remove socio-economic variables (other than age) that do not have a significant effect on loss aversion. The dummies for students and retired turn out to have no explanatory power, presumably because they are almost entirely explained by the age variables. We therefore drop these dummies. With regard to loss aversion in the cost dimension, we exclude education, gender, and income variables, as they are not significant. In the time dimension, we exclude the dummy for being out of work, which is not significant, and combine the two educational dummies, as they are similar in size. The above restrictions lead to Model 2 (the likelihood ratio test for the reduction from Model 1 to Model 2 has a p-value of 0.96). The restrictions cause the dummy for the age group ”below 25” to become significant in the cost dimension, otherwise the estimates do not change significantly from Model 1 to Model 2.

In the second step, we exclude age dummies that are not significant and combine age dummies for adjacent intervals if they are similar in size (Model 3, p-value for likelihood ratio test against Model 2: 0.55). In the third step, leading to our preferred model, Model 4, we exclude the frequency dummies for the first experiment, the reference travel cost, and, in the cost dimension, the reference travel time (p-value for likelihood ratio test against Model 3: 0.61). Note that upon removing reference cost, reference travel time becomes significant in the time dimension. Likely, this is due to the high correlation between reference travel time and reference cost.[15]

We note that the size of the travel time saving Δt has a significantly positive effect on the log MRS, both when considering time losses and time gains. Although not consistent with Hicksian preferences, where the marginal rate of substitution is a monotonic function of the total amount of a good, it is a common finding in surveys measuring trade-offs between travel time and money (Fosgerau et al., 2007; Mackie et al., 2003; Hultkrantz and Mortazavi, 2001; Gunn, 2001). We refer to the discussion in De Borger and Fosgerau (2008), who show how this effect can arise from curvature of the value functions under prospect theory.

The estimated constants in Model 4 correspond to the degrees of loss aversion of a person who is above 55 years of age, a male worker with a log income equal to the sample mean, whose highest education is primary/lower secondary school or vocational training, and whose real base trip is uncongested.[16] In SP1, this person has $\eta_t = 0.65$ and $\eta_c = 0.23$ This means that a time loss is valued $\exp(2\eta_t) = 3.7$ times higher than an equally sized time saving, while a cost increase is valued $\exp(2\eta_c) = 1.6$ times higher

[15] We tested whether the same was the case in the cost dimension - however, neither reference cost nor reference time became significant after removing the other.

[16] The sample mean of log income is 11.95, corresponding to a net income of around 155,000 DKK.

than a cost saving of the same size. If we did not control for loss aversion, we would observe a WTA-WTP ratio of $\exp(2\eta_t + 2\eta_c) = 5.9$.

Determinants of loss aversion in the time dimension

As already mentioned, occupation does not affect the degree of loss aversion in the time dimension in a significant way.

The degree of loss aversion increases with age, and age groups "below 25", "25-34", and "35-44" are all significantly less loss averse than subjects aged 45 and above. People with high school or higher education as latest finished education are significantly less loss averse than people with primary/lower secondary school or vocational training.

Still in the time dimension, we find that women are less loss averse than men, and that people with a higher income are less loss averse, but neither effect is significant.

As can be seen from comparing Model 3 and Model 4, there is not much difference between frequent and infrequent trips in SP1, where the reference is a recent trip. For SP2, where the reference may be hypothetical or less recent, people who know the reference situation better exhibit a significantly higher degree of loss aversion. People who never made the alternative base trip are not significantly different from people who rarely make the alternative base trip (base group).

As indicated by the experiment dummy, the degree of loss aversion is generally lower in the second experiment. Moreover, the degree of loss aversion decreases with reference travel time, and with the share of congestion on the real base trip. These effects are all significant.

Determinants of loss aversion in the cost dimension

As mentioned above, neither gender nor income have significant effect on loss aversion in the cost dimension. The effect of age seems to resemble the pattern in the time dimension, i.e. the degree of loss aversion increases with age: Young people below 25 are significantly less loss averse than people above 55, and the age group "25-54" is in between, though not significantly different from people above 55.

The effect of trip frequency is very similar to that in the time dimension: As seen from the results of Model 3, loss aversion does not vary significantly with frequency in the first experiment, while in the second experiment people who know the reference situation better are more loss averse (significant at the 10 percent level). Contrary to the time dimension, people who never made the alternative base trip are significantly less loss averse with respect to cost than the base group.

The degree of loss aversion is generally lower in SP2 than SP1, as in the time dimension, but the difference - represented by the SP2 dummy - is not significant. Finally, people with congested real base trips are significantly less loss averse, while people out of work exhibit significantly higher loss aversion than workers.

4.4.5 Validity check

Clearly, our results may depend on the assumed functional form of the model. As a further check of the validity of the results, we compute a weaker, non-parametric measure of loss aversion, and regress this on the covariates in z_t and z_c.[17] This approach assumes that the MRS is constant across the observations of a given individual within a given experiment, corresponding to the indifference curves being linear. In this setting, a within-experiment comparison of a subject's WTP (EG) choices to his EL (WTA) choices can in some circumstances reveal a pattern that would correspond to a preference reversal in a model that does not allow loss aversion, but can be explained by loss aversion in the time dimension. The measure of loss aversion in the time dimension, λ_t, is defined as the frequency of such "reversals" – see the Appendix for details. We define a measure of loss aversion in the cost dimension, λ_c, in a similar way, by comparing EG (WTA) choices to WTP (EL) choices.

Table 4.5 in the Appendix shows the OLS estimates of regressing λ_t and λ_c on z_t and z_c, respectively (full covariate vectors, corresponding to Model 1 above). The size of the estimated parameters cannot be compared directly to those in Table 4.3, since the two loss aversion measures have different scales, but we note that the results in general are similar with respect to sign: There are a few sign differences, but mostly such that none of the corresponding parameters are significantly different from zero, and never such that the two parameters are both significantly different from zero. Where we have groups of variables (age and trip frequency), the patterns of effects are also similar for the two approaches. The standard errors are generally larger in the OLS regressions because there is little variation in the dependent variables. Overall, the comparison of results does not reveal any systematic misspecification in our discrete choice model.

4.5 Discussion

In this paper, we investigated how loss aversion with respect to travel time and travel cost in two stated preference experiments varies with individual characteristics and between the experiments.

Before discussing our results, a comment on our data is in place: It is somewhat unusual to use survey data to investigate behavioural anomalies as loss aversion. Such analyses are often carried out using laboratory experiments, with two important advantages: First, it is possible to provide subjects with an incentive to reveal their true preferences. Second, reference points can be induced and varied, enabling the researcher to identify loss aversion separately from other preference curvature, as in Bateman et al. (1997) and Bateman et al. (2005). Here, however, we need a large data set to identify the factors affecting loss aversion. In such a large-scale experiment it is difficult and perhaps impossible to induce reference points specified by certain travel times in a realistic way. For the same reason, it is difficult to design an experiment that is incentive-compatible: To achieve this, subjects in the experiment should know that they would experience the consequence of their actions, and this is unrealistic when the consequence is a cer-

[17] We thank an anonymous referee for suggesting this method.

tain travel time, and all other characteristics of the trip, such as comfort, scenery, and congestion level, must be as specified in the choice problem.

Overall, we found significant loss aversion in both the time and cost dimensions – for a representative individual, time losses are valued 3.7 times higher than equally-sized time savings, while cost increases are valued 1.6 times higher than cost savings of the same size. This corresponds to a WTA-WTP ratio of 5.9. The representative individual has a higher degree of loss aversion with respect to time than with respect to costs, in accordance with the empirical findings in Horowitz and McConnell (2002), where the WTA-WTP gap is large for goods that are not often traded in a market, and small for market goods and money. This effect is consistent with the evidence that trading experience reduces loss aversion, as subjects are more used to trading with money than with travel time.[18]

We found that the degree of loss aversion in the travel time dimension increases with age and decreases with education, which is consistent with the findings of Johnson et al. (2006), Gächter et al. (2007) and Booij and van de Kuilen (2009). Like Booij and van de Kuilen (2009), and in contrast with Johnson et al. (2006) and Gächter et al. (2007), we find no significant effect of income, but we note that income and education are correlated. Like Johnson et al. (2006) and Gächter et al. (2007) we find no significant gender effect.

When comparing an experiment with a real-life reference point to an experiment with a more hypothetical reference point, the degree of loss aversion is lower when the reference is hypothetical. With the hypothetical reference, people who do not know their reference well, because they rarely make the alternative base trip, are less loss averse. These two findings suggest that loss aversion depends on how established the reference is in the mind of the choice maker: It appears that people tend to be more loss averse when the reference is well established.

Further, we found a significantly negative effect of congestion on loss aversion in both time and cost dimensions. This finding may indicate that subjects who experience congestion on their base trip have a different attitude towards gains and losses. We know that these subjects are likely to have experienced a range of different travel times for similar trips, since travel times tend to be more variable and unpredictable from day to day when there is congestion. It is possible that this experience somehow reduces the degree of loss aversion. But the causality could also go the other way, if loss aversion is positively correlated with risk aversion, since more risk averse individuals are likely to self-select into less congested trips.

The result could also, however, be an effect of the experimental design: We define losses and gains with respect to the subject's observed travel time on a given day, but if the journey is very congested, this observed travel time may not coincide with the subject's reference point (his perception of the "normal" travel time). On average, the

[18] An issue raised by a reviewer is whether loss aversion in the travel time dimension is confounded with rescheduling disutility: Usually, it is assumed that subjects react to a change in travel time by rescheduling to depart earlier or later, such that the marginal utility of being at the origin at departure time equals the marginal utility of being at the destination at arrival time (Fosgerau and Engelson, 2011). Hence, in equilibrium, the marginal utility of a change in travel time (u_t in eq. (4.2)) encompasses the marginal utility of rescheduling, implying that the latter is not confounded with loss aversion.

deviation should be increasing with the level of congestion, meaning that the congestion variable would pick up the effect on the measured degree of loss aversion.

We would like to compare our results to theoretical predictions, but there appears to be little consensus regarding the source of loss aversion. One potential explanation, as suggested by Johnson et al. (2006), was formulated in the *query theory* of Johnson et al. (2007). This theory proposes that the process of valuing a gain is different from that of valuing a loss. The two processes involve the same queries, but execute them in different order. Based on evidence from memory research, Johnson et al. (2007) suggested that output interference (that the recall of a member from a list results in a decrease in memory for other members) causes the two processes to yield different valuations. Based on query theory, we would expect that different levels of cognitive ability, specifically with regards to the short-term memory, may cause more or less interference between the two valuations, i.e. varying degree of gain-loss discrepancy. So, individuals with better cognitive abilities would exhibit a lower degree of loss aversion. Taking education as a proxy for cognitive abilities, our results are consistent with this hypothesis.

Another potential source of loss aversion is that the subject may perceive the outcomes of the choice as ambiguous or uncertain. He may be uncertain about the utility yielded by consuming a chosen bundle of goods, either because the exact conditions under which consumption will actually take place are not known at the moment of making the choice, or because he to some extent is uncertain about his own preferences. The *taste uncertainty theory* of Loomes et al. (2009) explains how such uncertainty may cause loss averse behaviour. The theory predicts a positive relation between the strength of loss aversion and the level of uncertainty associated with the choice outcomes, and hence offers an explanation of why trading experience should reduce loss aversion. A similar theory is developed by Fosgerau and De Borger (2009), using Gilboa and Schmeidler (1989): Assuming that the subject is uncertain or ambiguous about any outcome different from the reference point, and pessimistic in the sense that he maximises the minimum (reference-free) utility over all outcomes, they show that choices are rationalized by a function that is kinked at the reference, such that losses are overweighted relative to gains. In their model, ambiguity concerning the non-reference outcomes will increase loss aversion, predicting that trading experience should reduce loss aversion.

Likely, one of these theories can be extended to predict how ambiguity concerning the reference will affect loss aversion, but in their present form, this is not obvious. Our finding that people tend to be more loss averse when the reference is well established, therefore yet lacks theoretical support.

References

Arkes, H., Hirshleifer, D., Jiang, D., Lim, S., 2008. Reference point adaptation: Tests in the domain of security trading. Organizational Behavior and Human Decision Processes 105, 67–81. [64]

Bateman, I., Kahneman, D., Munro, A., Starmer, C., Sugden, R., 2005. Testing competing models of loss aversion: an adversarial collaboration. Journal of Public Economics 89, 1561–1580. [64, 79]

Bateman, I., Munro, A., Rhodes, B., Starmer, C., Sugden, R., 1997. A test of the theory of reference-dependent preferences. Quarterly Journal of Economics 112, 479–505. [63, 64, 71, 79]

Booij, A. S., van de Kuilen, G., 2009. A parameter-free analysis of the utility of money for the general population under prospect theory. Journal of Economic Psychology 30, 651–666. [64, 65, 80]

Brooks, P., Zank, H., 2005. Loss averse behavior. Journal of Risk and Uncertainty 31, 301–325. [64, 65]

Chamberlain, G., 1984. Panel data. In: Griliches, Z., Intriligator, M.D. (Eds), *Handbook of Econometrics, Vol 2*, Elsevier, pp. 1247 – 1318. [75]

De Borger, B., Fosgerau, M., 2008. The trade-off between money and travel time: A test of the theory of reference-dependent preferences. Journal of Urban Economics 64, 101–115. [67, 71, 77]

Doornik, J. A., 2001. Ox: An Object-Oriented Matrix Programming Language. Timberlake Consultants Press London. [77]

Fosgerau, M., 2007. Using nonparametrics to specify a model to measure the value of travel time. Transportation Research Part A 41, 842–856. [69]

Fosgerau, M., De Borger, B., 2009. Hedonic preferences, symmetric loss aversion and the willingness to pay - willingness to accept gap. International Choice Modelling Conference, Harrogate 2009. [67, 81]

Fosgerau, M., Engelson, L., 2011. The value of travel time variance. Transportation Research Part B: Methodological 45 (1), 1 – 8. [80]

Fosgerau, M., Hjorth, K., Lyk-Jensen, S. V., 2007. The Danish Value of Time Study: Final report. Report for the Danish Ministry of Transport, Danish Transport Research Institute. [69, 77]

Gächter, S., Johnson, E., Herrmann, A., 2007. Individual-level loss aversion in riskless and risky choices. Discussion Paper No. 2007-02, Centre for Decision Research and Experimental Economics, University of Nottingham. [64, 65, 80]

Gilboa, I., Schmeidler, D., 1989. Maxmin expected utility with non-unique prior. Journal of Mathematical Economics 18, 141–153. [81]

Gunn, H., 2001. Spatial and temporal transferability of relationships between travel demand, trip cost and travel time. Transportation Research Part E 37, 163–189. [77]

Harrison, G. W., Rutström, E. E., 2008. Risk aversion in the laboratory. In R. M. Isaac and D. A. Norton (Eds) *Risk Aversion in Experiments (Research in Experimental Economics, Volume 12)*, Emerald Group Publishing Limited, pp. 41 – 196. [64, 65]

Harrison, G. W., Rutström, E. E., 2009. Expected utility theory and prospect theory: one wedding and a decent funeral. Experimental Economics 12, 133–158. [64, 65]

Horowitz, J. K., McConnell, K. E., 2002. A review of WTA/WTP studies. Journal of Environmental Economics and Management 44, 426–447. [63, 66, 80]

Horowitz, J. K., McConnell, K. E., 2003. Willingness to accept, willingness to pay and the income effect. Journal of Economic Behavior and Organization 51, 537–545. [63]

Hultkrantz, L., Mortazavi, R., 2001. Anomalies in the value of travel-time changes. Journal of Transport Economics and Policy 35, 285–300. [77]

Isoni, A., Loomes, G., Sugden, R., 2011. The willingness to pay-willingness to accept gap, the 'endowment effect', subject misconceptions, and experimental procedures for eliciting valuations: Comment. American Economic Review 101, 991–1011. [66]

Johnson, E., Gächter, S., Herrmann, A., 2006. Exploring the nature of loss aversion. Discussion Paper No. 2015, Institute for the Study of Labor, Bonn. [64, 65, 80, 81]

Johnson, E., Häubl, G., Keinan, A., 2007. Aspects of endowment: A query theory of value construction. Journal of Experimental Psychology: Learning, Memory, and Cognition 33, 461–474. [81]

Kahneman, D., Knetsch, J. L., Thaler, R. H., 1990. Experimental tests of the endowment effect and the Coase theorem. Journal of Political Economy 98, 1325–1348. [64]

Köbberling, V., Wakker, P., 2005. An index of loss aversion. Journal of Economic Theory 122, 119–131. [67]

Köszegi, B., Rabin, M., 2004. A model of reference-dependent preferences. Department of Economics, University of California, Berkeley, Working Paper No. 1061, 2004. [64]

Köszegi, B., Rabin, M., 2006. A model of reference-dependent preferences. The Quarterly Journal of Economics 121, 1133–1165. [64, 67]

Li, Q., Racine, J., 2007. Nonparametric Econometrics: Theory and Practice. Princeton University Press. [73]

List, J. A., 2005. Scientific numerology, preference anomalies, and environmental policymaking. Environmental and Resource Economics 32, 35–53. [64, 66]

List, J. A., 2007. Neoclassical theory versus prospect theory: Evidence from the marketplace. Econometrica 72, 615–625. [64, 66]

Loomes, G., Orr, S., Sugden, R., 2009. Taste uncertainty and status quo effects in consumer choice. Journal of Risk and Uncertainty 39, 113–135. [81]

Loomes, G., Starmer, C., Sugden, R., 2003. Do anomalies disappear in repeated markets? The Economic Journal 113, C153–C166. [64, 66]

Loomes, G., Starmer, C., Sugden, R., 2010. Preference reversals and disparities between willingness to pay and willingness to accept in repeated markets. Journal of Economic Psychology 31, 374–387. [64, 66]

Mackie, P., Fowkes, A., Wardman, W., Whelan, G., Nellthorp, J., Bates, J., 2003. Value of travel time savings in the UK – summary report. Report to Department for Transport. Institute for Transport Studies, University of Leeds in association with John Bates Services. [77]

Munro, A., Sugden, R., 2003. On the theory of reference-dependent preferences. Journal of Economic Behavior and Organization 50, 407–428. [67]

Plott, C. R., Zeiler, K., 2005. The willingness to pay - willingness to accept gap, the 'endowment effect', subject misconceptions, and experimental procedures for eliciting valuations. The American Economic Review 95, 530–545. [64, 66]

Sayman, S., Öncüler, A., 2005. Effects of study design characteristics on the WTA-WTP disparity: A meta analytical framework. Journal of Economic Psychology 26, 289–312. [63, 66]

Schmidt, U., Traub, S., 2002. An experimental test of loss aversion. Journal of Risk and Uncertainty 25, 233–249. [64, 65]

Wooldridge, J., 2002. Econometric Analysis of Cross Section and Panel Data. MIT Press, Cambridge, MA. [75]

Appendix

Derivation of equations (4.10), (4.11), and (4.12)

In the following, we omit the subscripts i and s. Due to the experimental design, either c_1 or c_2 will be equal to c_0. This implies that

$$\Delta V_c = \exp(\eta_c S(c))|c|.$$

Recall that, when $t_0 > 10$ minutes, the choice types are determined relative to the base trip (t_0, c_0) rather than (t_0+2, c_0). Hence either t_1 or t_2 will be equal to t_0, and so

$$\Delta V_t = \exp(\eta_t S(t))|t|.$$

In this case, we can write eq. (4.6) as

$$y = 1 \iff \log w + \eta_t S(t) + \log|t| - \eta_c S(c) - \log|c| > \frac{\varepsilon}{\mu}.$$

When $t_0 \leq 10$ minutes, choice types are determined relative to (t_0+2, c_0), and we have for WTP and EG choices that $t_1 < t_0 < t_2 = t_0 + 2$. Hence

$$\Delta V_t = 2\exp(\eta_t) + \exp(-\eta_t)|t_1 - t_0|.$$

Here, eq. (4.6) can be rewritten as

$$y = 1 \iff \log w + \log(2\exp(\eta_t) + \exp(-\eta_t)|t_1 - t_0|) - \eta_c S(c) - \log|c| > \frac{\varepsilon}{\mu}.$$

For WTA and EL choices, $t_0 + 2 = t_1 < t_2$, and

$$\Delta V_t = \exp(\eta_t)(t_2 - t_0 - 2).$$

So in this case eq. (4.6) can be rewritten as

$$y = 1 \iff \log w + \eta_t + \log(t_2 - t_0 - 2) - \eta_c S(c) - \log|c| > \frac{\varepsilon}{\mu}.$$

Equations (4.10), (4.11), and (4.12) now follow from inserting the expressions for w, η_t, and η_c (equations (4.7), (4.8), and (4.9)).

Validity check - computation of λ_t and λ_c

The measure of loss aversion in the time dimension, λ_t, is defined for each individual in each experiment as $\lambda_t = \frac{|R_t|}{|N_t|}$, where N_t is the set of choice pairs where we would be able to detect loss aversion, i.e. pairs where (recall that $v = \frac{\Delta c}{\Delta t}$ is the trade-off price of time)

- one choice is WTP, the other EL, and $v_{\text{WTP}} \leq v_{\text{EL}}$, or
- one choice is EG, the other WTA, and $v_{\text{EG}} \leq v_{\text{WTA}}$.

Note that, with linear indifference curves, and in the absence of loss aversion, an individual would choose the fast alternative in the WTP (EG) choice if he chooses the fast alternative in the EL (WTA) choice (by eq. (4.3), choosing the fast alternative in the EL choice is equivalent to $MRS > v_{\mathrm{EL}}$, implying that $MRS > v_{\mathrm{WTP}}$, which is equivalent to choosing the fast alternative in the WTP choice). $R_t \subseteq N_t$ is the subset of N_t, where this condition is violated in a way consistent with loss aversion in the time dimension, i.e. where the cheaper alternative is chosen in the WTP (EG) choice and the faster alternative is chosen in the EL (WTA) choice.

We define a measure of loss aversion in the cost dimension, λ_c, in a similar way, by comparing EG (WTA) choices to WTP (EL) choices.

Tables

Table 4.2: Descriptive Statistics

Variable	Unit/Type	Mean	Std.dev.	Min	Max
$(\log \Delta t) \times \{t > 0\}$	log minutes	0.99	1.07	0.00	4.09
$(\log \Delta t) \times \{t < 0\}$	log minutes	0.91	1.10	0.00	4.09
SP2 dummy	dummy	0.18	0.38	0.00	1.00
age < 25	dummy	0.06	0.24	0.00	1.00
$25 \leq$ age < 35	dummy	0.15	0.36	0.00	1.00
$35 \leq$ age < 45	dummy	0.22	0.41	0.00	1.00
$45 \leq$ age < 55	dummy	0.18	0.38	0.00	1.00
age ≥ 65	dummy	0.16	0.37	0.00	1.00
education = high school	dummy	0.08	0.27	0.00	1.00
education = higher	dummy	0.50	0.50	0.00	1.00
female	dummy	0.44	0.50	0.00	1.00
log(income) - demeaned	income is in DKK	0.00	3.24	-11.02	2.04
missing income	dummy	0.08	0.27	0.00	1.00
student	dummy	0.07	0.26	0.00	1.00
retired	dummy	0.24	0.43	0.00	1.00
out of work	dummy	0.06	0.24	0.00	1.00
SP1 $\times$ {freq=daily}	dummy	0.20	0.40	0.00	1.00
SP1 $\times$ {freq=weekly}	dummy	0.21	0.40	0.00	1.00
SP2 $\times$ {freq=daily/weekly}	dummy	0.01	0.08	0.00	1.00
SP2 $\times$ {freq=never}	dummy	0.08	0.27	0.00	1.00
share of congestion	takes values in [0,1]	0.07	0.13	0.00	0.68
log reference travel cost	log DKK	3.29	1.21	0.00	6.75
log reference travel time	log minutes	3.50	0.89	1.61	5.89
c	DKK	0.29	16.24	-200.00	175.00
t	minutes	0.55	12.66	-60.00	60.00
S(c)	takes values in {-1,0,1}	0.00	1.00	-1.00	1.00
S(t)	takes values in {-1,0,1}	0.07	1.00	-1.00	1.00

Table 4.3: Estimation results (Models 1-2) – Fixed effects logit estimates

Parameter	Model 1 Estimate	Model 1 Std.Err.		Model 2 Estimate	Model 2 Std.Err.	
β's corresponding to:						
$(\log \Delta t) \times \{t > 0\}$	0.4897	0.0386	***	0.4899	0.0386	***
$(\log \Delta t) \times \{t < 0\}$	0.3155	0.0397	***	0.3167	0.0397	***
γ_t's corresponding to:						
constant	0.6958	0.1180	***	0.6446	0.1112	***
SP2	-0.3283	0.0576	***	-0.3251	0.0575	***
age < 25	-0.2774	0.1065	***	-0.2944	0.0833	***
$25 \leq$ age < 35	-0.1782	0.0595	***	-0.1601	0.0548	***
$35 \leq$ age < 45	-0.1301	0.0529	**	-0.1092	0.0484	**
$45 \leq$ age < 55	0.0151	0.0548		0.0361	0.0514	
age ≥ 65	-0.0202	0.0626		-0.0485	0.0569	
education = high school	-0.1114	0.0667	*			
education = higher	-0.0730	0.0367	**			
education = high school or higher				-0.0773	0.0353	**
female	-0.0557	0.0348		-0.0559	0.0346	
log(income)	-0.0682	0.0418		-0.0464	0.0387	
income missing	-0.8773	0.4985	*	-0.6217	0.4615	
student	-0.0640	0.0894				
retired	-0.0750	0.0605				
out of work	-0.0448	0.0735				
SP1 $\times$ {freq=daily}	-0.0032	0.0489		0.0047	0.0483	
SP1 $\times$ {freq=weekly}	-0.0277	0.0481		-0.0285	0.0480	
SP2 $\times$ {freq=daily/weekly}	0.4635	0.2190	**	0.4753	0.2189	**
SP2 $\times$ {freq=never}	0.0453	0.0749		0.0363	0.0746	
share of congestion	-0.7479	0.1400	***	-0.7561	0.1400	***
log(reference time)	-0.0108	0.0459		-0.0145	0.0458	
log(reference cost)	-0.0474	0.0320		-0.0435	0.0318	
γ_c's corresponding to:						
constant	0.2233	0.0998	**	0.2368	0.0885	***
SP2	-0.0802	0.0554		-0.0800	0.0552	
age < 25	-0.1502	0.0978		-0.1834	0.0711	***
$25 \leq$ age < 35	-0.0030	0.0557		0.0036	0.0506	
$35 \leq$ age < 45	-0.0722	0.0500		-0.0608	0.0457	
$45 \leq$ age < 55	-0.0607	0.0517		-0.0503	0.0484	
$25 \leq$ age < 55						
age ≥ 65	-0.0093	0.0575		-0.0249	0.0514	
education = high school	0.0258	0.0627				
education = higher	-0.0132	0.0342				
female	0.0265	0.0327				
log(income)	0.0251	0.0389				
income missing	0.2999	0.4633				
student	-0.0539	0.0824				
retired	-0.0187	0.0566				
out of work	0.1394	0.0685	**	0.1456	0.0647	**
SP1 $\times$ {freq=daily}	-0.0674	0.0452		-0.0629	0.0448	
SP1 $\times$ {freq=weekly}	0.0213	0.0443		0.0221	0.0442	
SP2 $\times$ {freq=daily/weekly}	0.3812	0.2078	*	0.3879	0.2081	*
SP2 $\times$ {freq=never}	-0.1987	0.0731	***	-0.1970	0.0727	***
share of congestion	-0.3145	0.1275	**	-0.3190	0.1273	**
log(reference time)	0.0013	0.0391		0.0031	0.0388	
log(reference cost)	-0.0009	0.0293		-0.0009	0.0288	
μ (error scale)	1.3211	0.0304	***	1.3210	0.0303	***
Log likelihood value	-4681.1			-4683.2		
Number of estimated parameters	47			36		

***, ** and * indicate significance at the 1, 5 and 10 percent level, respectively.
The significance level of the error scale is relative to 1.

Table 4.4: Estimation results (Models 3-4) – Fixed effects logit estimates

	Model 3			Model 4		
Parameter	Estimate	Std.Err.		Estimate	Std.Err.	
β's corresponding to:						
$(\log \Delta t) \times \{t > 0\}$	0.4893	0.0386	***	0.4892	0.0386	***
$(\log \Delta t) \times \{t < 0\}$	0.3174	0.0397	***	0.3163	0.0397	***
γ_t's corresponding to:						
constant	0.6307	0.1049	***	0.6531	0.0913	***
SP2	-0.3239	0.0575	***	-0.3173	0.0553	***
age < 25	-0.2864	0.0778	***	-0.2822	0.0777	***
$25 \leq$ age < 35	-0.1626	0.0478	***	-0.1636	0.0476	***
$35 \leq$ age < 45	-0.1110	0.0406	***	-0.1135	0.0406	***
$45 \leq$ age < 55						
age ≥ 65						
education = high school						
education = higher						
education = high school or higher	-0.0787	0.0353	**	-0.0805	0.0353	**
female	-0.0497	0.0344		-0.0439	0.0341	
log(income)	-0.0343	0.0377		-0.0355	0.0374	
income missing	-0.4808	0.4502		-0.4930	0.4479	
student						
retired						
out of work						
SP1 $\times$ {freq=daily}	0.0110	0.0480				
SP1 $\times$ {freq=weekly}	-0.0285	0.0480				
SP2 $\times$ {freq=daily/weekly}	0.4754	0.2185	**	0.4872	0.2180	**
SP2 $\times$ {freq=never}	0.0342	0.0746		0.0291	0.0745	
share of congestion	-0.7515	0.1399	***	-0.7130	0.1368	***
log(reference time)	-0.0171	0.0458		-0.0641	0.0253	**
log(reference cost)	-0.0406	0.0318				
γ_c's corresponding to:						
constant	0.2265	0.0836	***	0.2302	0.0281	***
SP2	-0.0750	0.0550		-0.0661	0.0526	
age < 25	-0.1748	0.0678	***	-0.1829	0.0673	***
$25 \leq$ age < 35						
$35 \leq$ age < 45						
$45 \leq$ age < 55						
$25 \leq$ age < 55	-0.0311	0.0326		-0.0384	0.0323	
age ≥ 65						
education = high school						
education = higher						
female						
log(income)						
income missing						
student						
retired						
out of work	0.1491	0.0646	**	0.1574	0.0645	**
SP1 $\times$ {freq=daily}	-0.0583	0.0444				
SP1 $\times$ {freq=weekly}	0.0216	0.0442				
SP2 $\times$ {freq=daily/weekly}	0.3841	0.2080	*	0.3854	0.2076	*
SP2 $\times$ {freq=never}	-0.2006	0.0727	***	-0.2000	0.0722	***
share of congestion	-0.3179	0.1273	**	-0.3388	0.1250	***
log(reference time)	0.0022	0.0388				
log(reference cost)	-0.0001	0.0288				
μ (error scale)	1.3206	0.0303	***	1.3190	0.0302	***
Log likelihood value	-4685.2			-4687.9		
Number of estimated parameters	31			24		

***, ** and * indicate significance at the 1, 5 and 10 percent level, respectively.
The significance level of the error scale is relative to 1.

Table 4.5: Estimation results (Model 1) – OLS estimates of regression of λ_t and λ_c on z_t and z_c, respectively

	Time dimension			Cost dimension		
Parameter	Estimate	Std.Err.		Estimate	Std.Err.	
constant	0.2826	0.0620	***	0.1056	0.0638	*
SP2	-0.1216	0.0221	***	-0.0404	0.0226	*
age $<$ 25	-0.0733	0.0393	*	-0.0385	0.0411	
25 $\leq$ age $<$ 35	-0.0304	0.0222		-0.0073	0.0227	
35 $\leq$ age $<$ 45	-0.0491	0.0199	**	-0.0483	0.0203	**
45 $\leq$ age $<$ 55	-0.0032	0.0204		-0.0253	0.0207	
age $\geq$ 65	0.0143	0.0227		0.0303	0.0235	
education = high school	-0.0294	0.0255		0.0027	0.0262	
education = higher	-0.0257	0.0137	*	-0.0259	0.0140	*
female	-0.0088	0.0130		0.0324	0.0133	**
log(income)	0.0001	0.0156		0.0326	0.0161	**
income missing	0.0174	0.1861		0.4355	0.1915	**
student	-0.0201	0.0335		-0.0401	0.0347	
retired	-0.0144	0.0224		0.0025	0.0230	
out of work	0.0401	0.0269		0.0550	0.0281	*
SP1 x {freq=daily}	0.0027	0.0182		0.0072	0.0188	
SP1 x {freq=weekly}	-0.0313	0.0176	*	0.0142	0.0180	
SP2 x {freq=daily/weekly}	0.1130	0.0819		0.1879	0.0835	**
SP2 x {freq=never}	0.0195	0.0293		0.0159	0.0301	
share of congestion	-0.0668	0.0522		0.0557	0.0538	
log(reference time)	0.0161	0.0156		-0.0025	0.0164	
log(reference cost)	-0.0133	0.0117		0.0017	0.0122	
R^2	0.0440			0.0285		
Number of estimated parameters	22			22		

***, ** and * indicate significance at the 1, 5 and 10 percent level, respectively.
Note that standard errors are possibly underestimated; they are computed assuming independent observations, though we have two observations for each subject participating in SP2 - one for each experiment.

Chapter 5

Cumulative prospect theory applied to stated preference data with travel time variability

Cumulative prospect theory applied to stated preference data with travel time variability

Katrine Hjorth

Abstract

Preferences for travel time variability are often measured using stated preference (SP) data from choice tasks where travel time distributions are given by a list of equally likely outcomes. Most studies assume that travellers' choices maximise their expected utility.

The current paper analyses data from such an experiment, applying a discrete choice model based on cumulative prospect theory, which accommodates reference-dependence and rank-dependent probability weighting. We model choice behaviour using a logit framework, and find significant evidence of loss aversion and probability weighting: Respondents do not behave as if they maximize expected utility, but appear to overweight the likelihood of extreme outcomes.

Acknowledgements

The author would like to thank Farideh Ramjerdi and Stefan Flügel for valuable comments.

5.1 Introduction

In this paper, we analyse travellers' hypothetical route choices in a stated preference (SP) experiment where the travel times on the routes are unknown, but follow known probability distributions. In contrast with what is usually assumed in studies of such data, we demonstrate that respondents do not behave as if they maximize expected utility, but appear to overweight the likelihood of extreme outcomes.

Travel time variability (TTV) denotes the randomness in travel time a traveller faces when deciding when, where, and how to travel. Preferences for TTV is a "hot" topic in the transport economics literature: The research is motivated by the huge cost TTV inflicts on society, making it necessary to account for TTV in traffic forecasts and cost-benefit analyses of transport projects. The current state-of-the-art research in the field is involved with developing a theoretically sound practice of measuring travellers' preferences for TTV.

One popular approach – which we refer to as the direct approach – to model travellers' mode, route, and departure time choice, is to model travel choice directly as a function of the travel time distribution and the traveller's risk attitude. Some studies assume that travellers maximise the expected CARA or CRRA utility of travel time (de Palma and Picard, 2005, 2006); others that the choice is a function of the mean or

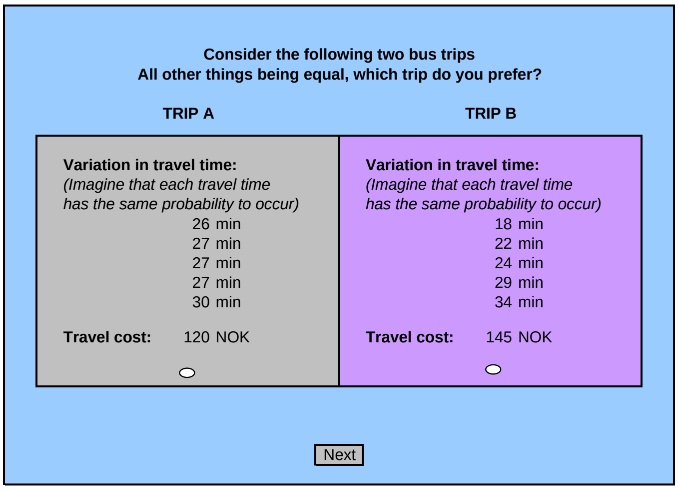

Figure 5.1: Example of choice task with five equally likely outcomes (Ramjerdi et al., 2010)

median travel time and a measure of the TTV, e.g. variance, standard deviation, interquantile distance, or, for public transport modes, the probability of delay relative to schedule (Lam and Small, 2001; Rietveld et al., 2001; Brownstone and Small, 2005; Small et al., 2005).

Another approach – the so-called scheduling approach – models choice as a function of the traveller's utility of the travel time outcomes, in terms of the time the traveller spends at home, under way, and at the destination. Some scheduling models, based on Vickrey (1969) and Small (1982), assume the traveller has a fixed preferred arrival time (PAT) and that his utility decreases in the amount of time he arrives earlier or later than this (Noland and Small, 1995; Noland et al., 1998; Small et al., 1999; Bates et al., 2001; Noland and Polak, 2002; Hollander, 2006; Hensher et al., 2011). Other scheduling models, based on Vickrey (1973), assume that the traveller's utility increases with a diminishing rate with his departure time and decreases with an increasing rate with his arrival time (Tseng and Verhoef, 2008; Fosgerau and Engelson, 2011).

Generally, preferences are measured using SP data. The literature has seen a variety of choice formats, representing variability in different manners, and has not reached consensus regarding a preferable format (see, e.g. de Jong et al., 2007; Fosgerau et al., 2008). On one hand, the choice tasks should be so simple that respondents can relate to them; on the other hand, they should be sufficiently realistic to be of use in forecasts and cost-benefit analyses. An often applied format is to present respondents with travel time distributions given by five or more equally likely outcomes, as in Figures 5.1 and 5.2. Typically, the choice format depends on whether the direct approach or the scheduling approach is intended for analysis: In the latter case, choices involve scheduling elements as departure/arrival times or delays.

A common feature for most studies is that they assume that travellers' choices maximise their expected utility. On the other hand, the economic literature of decision under risk uses more sophisticated behavioural models that accommodate "anomalies" as probability weighting or reference-dependence: Prospect theory, rank-dependent util-

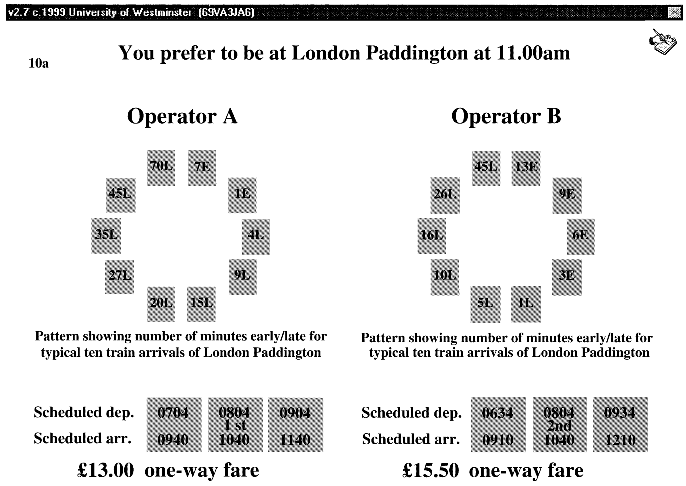

Figure 5.2: Example of choice task with ten equally likely outcomes (Bates et al., 2001)

ity theory, cumulative prospect theory (Kahneman and Tversky, 1979; Quiggin, 1982; Tversky and Kahneman, 1992), and newer theories as the model in Köszegi and Rabin (2007). Several studies have tested the descriptive power of the models, comparing them to each other and to expected utility theory (Hey and Orme, 1994; Harless and Camerer, 1994; Loomes et al., 2002; Stott, 2006; Harrison and Rutström, 2009).

The large majority of the economic literature about risk attitudes and choice under risk concerns itself with preferences for money, often studied using laboratory experiments where subjects make choices involving lotteries (for a recent review of methodology, see Harrison and Cox, 2008).

Avineri and Prashker (2004) perform a laboratory experiment where subjects make hypothetical choices between two routes with different travel time distributions, and demonstrate that subjects violate expected utility theory (EUT) in two ways: An extreme underweighting of high probabilities, which fall short of certainty (certainty effect), and an overweighting of small probabilities. Such behaviour is consistent with prospect theory, rank-dependent utility theory (RDUT) and cumulative prospect theory (CPT). The experiment resembles a classical experimental economics study [1], in that it is designed to reveal specific anomalies for specific framings of the choice context, rather than to measure preferences for TTV over a broad range of attribute values to estimate its effect on behaviour, as is usually the case in the transport literature. It therefore deviates from the general TTV SP studies in that all alternatives have the same monetary cost (implicit), and that there is no attribute variation between subjects (all receive the same six choice tasks). Moreover, the sample is quite small (71 individuals). Nonetheless, the results imply that we cannot take for granted that respondents in SP experiments about TTV act in accordance with EUT. This may affect not just the economic analysis, but also the way these SP experiments are designed: If it turns out that respondents weight travel time outcomes differently from what the experimenter intends, the results

[1] The choice tasks are identical to selected choice tasks from Kahneman and Tversky (1979), except that travel time replaces monetary pay-offs as the good in question.

from the SP experiments cannot be applied in forecasts and welfare analyses, since we cannot be sure how the outcome weighting in the SP experiment is related to travellers' behaviour in real life.

Within the last decade, RDUT and CPT have been applied to different areas of the transport literature (see, e.g., Avineri and Bovy, 2008; Timmermans, 2010). However, to the best of our knowledge, there is but a few applications to SP studies measuring preferences for TTV: RDUT models (which accommodate rank-dependent probability weighting, but not reference-dependence) have been applied in two studies using the scheduling approach (Michea and Polak, 2006; Hensher and Li, 2011) and a single study using the direct approach (de Lapparent and Ben-Akiva, 2011).[2] [3] The evidence from these studies is mixed: Michea and Polak (2006) find significant probability weighting, but in opposite directions for different formulations of the utility function. Hensher and Li (2011) find that the probability of on-time arrival is underweighted compared to being either early or late, while de Lapparent and Ben-Akiva (2011) find that commuters tend to overweight the worst of two possible travel time outcomes.

The current paper extends this literature by applying a CPT model, which accommodates both rank-dependent probability weighting and reference-dependence, to data from a standard TTV SP experiment. We consider SP data from route choice tasks as in Figure 5.1, where travel alternatives are characterized by a monetary cost and a discrete travel time distribution with five mass points. The choice tasks do not involve scheduling components as departure and arrival times, so we consider choice to be a function of the cost and travel time distribution only, as in the direct approach. To define the context of the choice tasks, respondents are initially asked to report details about a recent trip, and then instructed to pretend they are to make the trip again, but now facing different travel times and costs. Because of this emphasis on the recent trip, it seems fair to assume that it serves as a reference point for preference formation in the choice tasks. In particular, the travel time and cost of the reference trip serve as natural reference points for the valuation of the time and cost attributes. In contrast, scheduling models usually define choice as a function of early and late delay (the amount of time the traveller arrives before or after PAT), for which the reference level is rarely known – making it is questionable whether it makes sense to apply CPT in that setting (see also the discussion of reference points in Timmermans, 2010).

Our results are consistent with the behavioural premises from cumulative prospect theory in that we find significant loss aversion with respect to travel time and diminishing sensitivity with respect to gains and losses in both time and cost dimensions. We do not observe loss aversion with respect to cost, where there is little difference between gains and losses.

Moreover, we find significant probability weighting, in the sense that allowing for probability weighting turns out to be a significant improvement of the explanatory power

[2] Michea and Polak (2006) actually intend to apply cumulative prospect theory, which allows for reference-dependence, but since they apply CPT (attribute-wise) to valuations of early and late delay (the amount of time the traveller arrives before or after PAT) and by definition only consider losses, this effectively corresponds to a RDUT model.

[3] Another paper (Hensher et al., 2011), similar to Hensher and Li (2011) and using similar SP data, apply direct (i.e. not rank-dependent) probability weighting.

of the behavioural model, compared to a model without probability weighting. Our results vary, depending on the assumed functional form of the weighting function, but indicate that respondents tend to overweight the likelihood of extreme outcomes (largest gain, smallest gain, smallest loss, and largest loss).

The paper is organised as follows. Section 5.2 presents the theoretical model, section 5.3 the data, and section 5.4 our analysis. Section 5.5 concludes.

5.2 Theoretical Model

Our model is based on the cumulative prospect theory model in Tversky and Kahneman (1992), applied attribute-wise to travel time and cost.

Consider a traveller and a given trip, the reference trip. We assume that the traveller has a reference travel time and a reference cost for this trip, representing his normal state or his expectations regarding the trip. We analyse the situation, where the respondent chooses between two trips that are identical to the reference trip, except for the travel time and cost. The two alternatives are each characterised by a discrete travel time distribution and a monetary cost. We do not know anything about the traveller's departure or arrival times under the alternatives, so we simply model his choice as a function of the travel time distributions and the costs, as in the direct approach. This is not the same as to say that departure and arrival times do not matter; we just interpret our model as a reduced form of a scheduling model.[4]

Let c_k denote the cost and $\{t_{kj}, p_{kj}\}_{j=1}^{n_k}$ the travel time distribution of alternative k: $t_{k1} \dots t_{kn_k}$ are distinct outcomes that occur with probabilities $p_{k1} \dots p_{kn_k}$, and $\sum_{j=1}^{n_k} p_{kj} = 1$. We normalise the reference travel time to zero, such that negative outcomes are faster than the reference (gains) and positive outcomes are slower than the reference (losses). Similarly, we normalise the reference cost to zero, such that c_k is negative when the alternative is cheaper than the reference (gain), and positive when more expensive (loss).

We assume that the respondent chooses the alternative that yields the higher CPT value $CPT(c_k, \{t_{kj}, p_{kj}\}_{j=1}^{n_k})$, except for a symmetric random error ε with mean zero; i.e. alternative 1 is chosen whenever

$$(5.1) \qquad CPT(c_1, \{t_{1j}, p_{1j}\}_{j=1}^{n_1}) > CPT(c_2, \{t_{2j}, p_{2j}\}_{j=1}^{n_2}) + \varepsilon.$$

We assume that the value of alternative k is additively separable in travel time and cost, such that it is given by

$$(5.2) \qquad CPT(c_k, \{t_{kj}, p_{kj}\}_{j=1}^{n_k}) = v_c(c_k) + \sum_{j=1}^{n_k} \pi_{kj} v_t(t_{kj}),$$

where the π's are cumulative decision weights, and the v's are non-increasing value functions that map costs or travel time outcomes to the set of real numbers. The value

[4] Fosgerau and Karlström (2010) and Fosgerau and Engelson (2011) show that the choice rule (or utility function) under the direct approach can in some cases be interpreted as a reduced form of the choice rule under the scheduling approach, achieved by assuming that travellers optimise their departure time given the travel time distribution. We have not formally ascertained whether this can also be done in our case.

functions are normalised such that $v(0) = 0$, implying that costs and travel time outcomes equal to the reference do not contribute to the CPT value.

As Tversky and Kahneman (1992), we assume that value functions are given by two-part power functions – one power function for gains, and another for losses. This approach has been criticized (see e.g. Wakker, 2010) because such functions are not differentiable at zero, and because of two unfortunate characteristics which hold whenever the gain and loss powers are not equal: First, the measured degree of loss aversion depends on the scaling of the attributes, and second, there will always be some outcome for which the gain value exceeds the loss value. Yet, the power functional is the most commonly applied form in the literature, and has also, in the few comparisons available, been found to have empirical support in terms of better goodness-of-fit (Stott, 2006). To avoid the above-mentioned unfortunate characteristics, we assume equal powers for gains and losses (as several others, see Wakker, 2010):

$$v_c(c) = \begin{cases} \beta_c^+(-c)^{\alpha_c} & \text{for } c \leq 0 \\ -\beta_c^-(c)^{\alpha_c} & \text{for } c > 0 \end{cases} \tag{5.3}$$

$$v_t(t) = \begin{cases} \beta_t^+(-t)^{\alpha_t} & \text{for } t \leq 0 \\ -\beta_t^-(t)^{\alpha_t} & \text{for } t > 0 \end{cases} \tag{5.4}$$

where the α's and β's are non-negative parameters. In the case of diminishing sensitivity, the curvature parameters (α's) will be smaller than 1. Gains are weighted by β^+, and losses are weighted by β^-. Respondents exhibit loss aversion for cost if $\beta_c^+ < \beta_c^-$, and for time if $\beta_t^+ < \beta_t^-$.

The decision weights are also reference-dependent. Outcomes equal to the reference ($t_{kj} = 0$) have weight zero: $\pi_{kj} = 0$, since they do not contribute to eq. (5.2) anyway. Using the notation from Wakker (2010), the decision weight for gains ($t_{kj} < 0$) is given by

$$\pi_{kj} = w^+(p_{kj} + r_{kj}^+) - w^+(r_{kj}^+), \tag{5.5}$$

where w^+ is an increasing weighting function that satisfies $w^+(0) = 0$ and $w^+(1) = 1$, and r_{kj}^+ is the gain rank of the outcome t_{kj}, defined as the cumulative probability of an outcome strictly better than t_{kj} :

$$r_{kj}^+ = \sum_{l=1}^{n_k} p_{kl} 1\{t_{kl} < t_{kj}\}. \tag{5.6}$$

For losses ($t_{kj} > 0$), the decision weight is given by

$$\pi_{kj} = w^-(p_{kj} + r_{kj}^-) - w^-(r_{kj}^-), \tag{5.7}$$

where, again, w^- is an increasing weighting function that satisfies $w^-(0) = 0$ and $w^-(1) = 1$, and r_{kj}^- is the loss rank of the outcome t_{kj}, defined as the cumulative probability of an outcome strictly worse than t_{kj} :

$$r_{kj}^- = \sum_{l=1}^{n_k} p_{kl} 1\{t_{kl} > t_{kj}\}. \tag{5.8}$$

We follow common practice and refer to w^+ and w^- as *probability weighting functions*, even though they are applied to ranks rather than probabilities. Likewise, we use the term *probability weighting* or *rank-dependent probability weighting* rather than *(outcome) rank weighting*.

In our analysis we apply the six weighting schemes 'NoW', 'TK1', 'TK2', 'Prl1', 'Prl2', and 'Prl3', defined in Table 5.1, which differ with respect to functional form, flexibility in terms of the number of parameters, and whether the same formulation is used for gains as for losses.

5.3 Data

Our data stem from a Norwegian survey conducted to establish values of travel time, variability, and traffic safety to be used in welfare-economic evaluations of transport infrastructure policies (Samstad et al., 2010; Ramjerdi et al., 2010). The respondents were recruited from a representative panel, and the survey was carried out on the Internet.

The survey covered both car trips, public transport (PT) trips and plane trips. In our analysis, we consider five combinations of transport mode and distance, which we analyse separately:

- Car short - car trips less than 100 km
- PT short - public transport trips less than 100 km
- Car long - car trips longer than 100 km
- PT long - public transport trips longer than 100 km
- Air - domestic plane trips

The survey contained several stated preference experiments, of which we use one: The choice experiment consists of six binary choices between travel alternatives that differ with respect to cost and the distribution of travel time. The latter is presented as a list of five equally likely travel times. Figure 5.1 illustrates how the alternatives are presented on the screen. The time and cost attributes are pivoted around the travel time and cost of a reference trip which the respondents report at the beginning of the survey. The reference trip is a one-way domestic trip for private purpose, carried out within the last week (for short distance segments) or within the last month (for long distance segments). Travel time is defined as in-vehicle time without stops, except for air travellers, where travel time is measured from airport to airport.

In our analysis, we exclude respondents who answered side-lexicographically (always chose left or right alternative), dropped out during the survey, or gave unrealistic reference values.[5] We also exclude air travellers with a reference travel time less than 80 minutes, because of an error in the questionnaire. These exclusions correspond to

[5] Unrealistic values are average speeds above 100 km per hour for land modes, average speeds above 1000 km per hour for air, cost less than 50 NOK for long distance modes, cost per kilometre less than 0.2 NOK or higher than 11 NOK for car modes.

Table 5.1: Weighting schemes

Scheme	Description	Formula	
NoW	No weighting. The weighting function is the identity function. No parameters.	$w^+(p) = w^-(p) = p$,	$p \in [0,1]$
TK1	From Tversky and Kahneman (1992). One parameter. The weighting function has an inverted S-shape if $\gamma < 1$, and is S-shaped for $\gamma \in]1,2[$.	$w^+(p) = w^-(p) = \frac{p^\gamma}{(p^\gamma+(1-p)^\gamma)^{1/\gamma}}$,	$p \in [0,1],\ \gamma > 0$
TK2	As above, but with different parameters for gains and losses.	$w^+(p) = \frac{p^{\gamma^+}}{(p^{\gamma^+}+(1-p)^{\gamma^+})^{1/\gamma^+}}$, $w^-(p) = \frac{p^{\gamma^-}}{(p^{\gamma^-}+(1-p)^{\gamma^-})^{1/\gamma^-}}$,	$p \in [0,1],\ \gamma^+ > 0$ $p \in [0,1],\ \gamma^- > 0$
Prl1	From Prelec (1998). One parameter. Inversely S-shaped, with fixed point $p = 1/e \approx 0.37$.	$w^+(p) = w^-(p) = \exp(-(-\ln p)^\theta)$,	$p \in (0,1],\ \theta \in (0,1]$
Prl2	From Prelec (1998). Two parameters. The weighting function can be convex, concave, S-shaped, or inversely S-shaped, and is more flexible than TK1 and Prl1.	$w^+(p) = w^-(p) = \exp(-\eta(-\ln p)^\theta)$,	$p \in (0,1],\ \eta, \theta > 0$
Prl3	As above, but with different η parameters for gains and losses. Three parameters. More flexible than TK2.	$w^+(p) = \exp(-\eta^+(-\ln p)^\theta)$, $w^-(p) = \exp(-\eta^-(-\ln p)^\theta)$,	$p \in (0,1],\ \eta^+, \theta > 0$ $p \in (0,1],\ \eta^-, \theta > 0$

around 9-11% of the observations for the car short, car long and PT long segments, and around 18-19% for PT short and air. Moreover, data are sparse for high values of reference time and cost, so we restrict our analysis to the following samples: [6]

- Car short: Cost $\leq$ 250 NOK, time $\leq$ 90 minutes.
- PT short: Cost $\leq$ 100 NOK, time $\leq$ 90 minutes.
- Car/PT long: Cost $\leq$ 1500 NOK, time $\leq$ 900 minutes.
- Air: Cost $\leq$ 5000 NOK, time $\leq$ 600 minutes, distance $\leq$ 3000 km.

Table 5.2 in the Appendix provides summary information of the resulting samples.

Recall from equations (5.5) and (5.7) that the decision weights of gain and loss outcomes in the CPT model depend on the weighting function w evaluated in $p+r$ and r, where w and r denote the appropriate (gain/loss) weighting function and rank. In our data, the five travel times presented for each alternative need not be distinct, and need not include the reference travel time. Moreover, they need not include both gains and losses. This implies that we observe a range of ranks r and outcome probabilities p for both gains and losses. Table 5.3 in the Appendix gives the distribution of all gain and loss outcomes on the corresponding pair $(p+r,r)$. As can be seen from Table 5.3, we have enough variation in ranks and outcome probabilities to identify w at the points 0.2, 0.4, 0.6, and 0.8. However, note that only around 20% of the non-reference outcomes involve w evaluated at 0.6 and 0.8 (the share being a little higher for losses, and a little lower for gains). This will affect the interpretation of our results.

5.4 Econometric analysis and results

Letting $y \in \{1,2\}$ denote the chosen alternative, the model can be written as

$$(5.9) \qquad y=1 \iff CPT(c_1,\{t_{1j},p_{1j}\}_{j=1}^{n_1}) > CPT(c_2,\{t_{2j},p_{2j}\}_{j=1}^{n_2}) + \varepsilon.$$

where $CPT(c_k,\{t_{kj},p_{kj}\}_{j=1}^{n_k})$ is as defined in section 5.2.

We estimate the parameters using maximum likelihood, assuming that the error term ε is logistic with scale parameter μ (inversely proportional to the standard deviation). For convenience, we assume that the error terms are independent across choices, including choices within the same individual, resulting in a binomial logit model.[7]

With μ being a free parameter, we need to normalise one of the other parameters to identify the model. We choose to normalise the cost gain parameter β_c^+ to 1. The advantage of normalising β_c^+ rather than μ is that we can directly compare parameter estimates from different data sets.

We estimate a separate set of parameter values for each of the five data segments. Estimation is carried out in Ox (Doornik, 2001), using 30 different sets of randomly

[6] 1 NOK $\approx$ 0.12 Euro.

[7] The independence assumption is convenient, but may be unrealistic: it would be violated if, e.g., respondents have heterogeneous preferences, such that choices within a given individual are correlated.

generated start values, to make sure we find the global optimum. The estimation results can be seen in Tables 5.4 - 5.9 in the Appendix. For the PT long segment, the Prl2 model does not converge to an optimal solution (the Hessian is singular), while the Prl1 model does not converge to a feasible solution (the value of θ at convergence is almost 42). In general, the estimated value functions for Prl1 and TK1 resemble those for NoW, and those for Prl2 are similar to those for Prl3, so we only show the value functions for NoW, TK2, and Prl3 models (Figures 5.3 - 5.8 in the Appendix). The estimated weighting functions are depicted in Figures 5.9 - 5.15 in the Appendix. The results for the PT short segment seem less reliable (high standard errors), and are not shown in the Figures.

5.4.1 Value functions

A consistent result, across data segments and weighting schemes, is that $\beta_t^+ < \beta_t^-$, indicating loss aversion with respect to travel time. In most cases the difference is very significant (LR tests, cf. Table 5.10 in the Appendix). In the single case (PT short, with TK2 weighting) where we do not observe loss aversion, the parameters are not significantly different. The ratio $\frac{\beta_t^-}{\beta_t^+}$ ranges from 0.8 to 10.9 over all segments and weighting schemes, cf. Table 5.11 in the Appendix. If we consider only the cases where β_t^+ and β_t^- are significantly different, the range is 1.3 - 10.9. Ignoring the PT short segment, where the ratios are much higher than for the remaining segments, most segments and models yield ratios around 1.5 - 3, in agreement with the findings from the literature.[8] In general, we observe the lowest ratios for the TK2 scheme and the highest ratios for the NoW scheme.

The curvature parameter of the value function for time (α_t) is generally significantly greater than zero and less than one (z-tests, 5% level), implying diminishing sensitivity to time changes.[9] We find the lowest values of α_t (corresponding to a more concave/convex value function in the gain/loss region) for the Prl2 and Prl3 schemes, and the highest values (corresponding to almost piece-wise linear value functions) for the Prl1, TK1, and NoW schemes (cf. Figures 5.3 - 5.5). Thus, it seems that allowing for more flexibility in terms of probability weighting results in a higher estimated degree of diminishing sensitivity.[10]

The curvature parameter of the value function for cost (α_c) varies very little across weighting schemes, but also tends to be lower for the Prl2 and Prl3 schemes than for the remaining schemes. With the exception of the PT short segment, where the cost value function is very poorly identified, α_c is also significantly greater than zero and less than one (z-tests, 5% level), implying diminishing sensitivity to cost changes. A

[8]See, e.g., the review in Booij et al. (2010). We can compare our β_t^-/β_t^+ ratio to their λ; though only for studies where the powers for gains and losses are roughly equal, cf. the discussion in Wakker (2010), sec. 9.6.

[9]The only exception is Air, NoW, where α_t is not significantly different from one.

[10]This is a sign that the parameter identification is not very strong: It is hard to identify value function curvature separately from the shape of probability weighting. Presumably, this is because our data lack the sufficient variation in the range of gains and losses for given ranks and outcome probabilities. This identification issue demands further investigation, but is left to future research.

consistent finding is that $\alpha_c < \alpha_t$, implying a higher degree of diminishing sensitivity for cost changes than time changes.

For the car long and PT long segments, we observe loss aversion with respect to money ($\beta_c^+ < \beta_c^-$) for all weighting schemes.[11] For the remaining segments, monetary gains are consistently valued at a higher rate than losses. However, as can be seen from Figures 5.6 - 5.8, the difference between gains and losses is small, and it is only significant for the large car short segment (LR tests, 5% level, cf. Table 5.10).

5.4.2 Probability weighting

In terms of model fit (LR tests, cf. Table 5.10), Prl and TK weighting schemes always perform significantly better than the NoW model at the 5% level, and almost always at the 1% level. However, we cannot ascertain whether the Prl or the TK scheme is better: In terms of the adjusted ρ^2 index, the Prl schemes seem to perform marginally better than the TK schemes, but they are almost equal.

In our interpretation of the weighting functions, we should take into account the relative lack of data with observations of $w(0.6)$ and $w(0.8)$: It is likely that the high end of the estimated weighting function is determined largely by the fitting of the assumed functional form to the low end; so we expect the estimated weighting of high ranks (cumulative probabilities) to be less reliable.[12]

We first focus on the weighting functions for losses and those common for gains and losses. The TK weighting schemes yield values of γ in the range from 0.67 to 0.82 for losses, and similar values when we estimate a common weighting function for gains and losses. The 95% confidence intervals are all within [0.57; 0.99], consistent with the findings in Tversky and Kahneman (1992) and other applications of this weighting scheme (see the review in Booij et al., 2010). The estimated parameters of the Prl weighting functions exhibit greater variation across segments. Omitting PT short, where the Prl weighting functions are poorly identified, we find values of θ and η consistent with those in the literature (again comparing to the review in Booij et al., 2010): Under Prl1, θ ranges from 0.31 to 0.47, while under Prl2 and Prl3, θ ranges from 1.12 to 2.54, and η from 0.19 to 0.55.

To interpret these estimates, we refer to Figures 5.9 - 5.13: We see that the results for the TK and Prl1 weighting schemes correspond to low ranks being overweighted and high ranks underweighted, while the results for the Prl2 and Prl3 schemes correspond to all ranks being overweighted. From the definition of the decision weights in equations (5.5) and (5.7), we see that the former pattern corresponds to overweighting the likelihood of the extreme outcomes (largest gain, smallest gain, smallest loss, and largest loss), and underweighting the likelihood of the remaining outcomes. The second pattern corresponds to overweighting the likelihood of the largest gain and the largest loss, and underweighting the likelihood of the remaining outcomes.

[11] Omitting Prl1 and Prl2 for PT long due to the convergence problems.

[12] Note that this is not reflected in the confidence limits in Figures 5.9 - 5.15, since these are based on the Delta method, and thus merely reflect the transformed confidence limits of the parameters γ, θ, and η.

Even though these two patterns at first glance seem quite different, they share their most reliable feature, namely that low ranks are overweighted, equivalent to overweighting the outcomes that yield the largest gain and the largest loss.

When estimating separate weighting functions for gains, the parameter estimates for gains exhibit larger variation across segments, and have larger standard errors. Under the TK2 scheme, the γ values for gains range from 1.75 to 6.25, and are always significantly higher than 1 (z-tests, 5% level). Under the Prl3 scheme, the η values for gains range from 0.44 to 0.92 (omitting the PT short segment). The TK2 results correspond to convex weighting functions, underweighting all ranks (Figure 5.14), which is equivalent to overweighting the smallest gain and underweighting the remaining gain outcomes. The Prl3 results (Figure 5.15), on the other hand, suggest linear or concave weighting functions. These results are however rather weak, as indicated by the confidence limits in Figure 5.15.

5.5 Conclusion

In this paper, we have applied a cumulative prospect theory model to data with travel time variability. We have assumed power functionals for value functions and six different probability weighting schemes based on the weighting functions in Tversky and Kahneman (1992) and Prelec (1998).

Overall, our results are consistent across the five data sets and seem reasonable: We find significant loss aversion with respect to travel time, where losses are valued roughly 1.5 to 3 times higher than gains, depending on the data set considered, and the assumptions made on the weighting function. This result corresponds well with the findings in the literature. We find no significant loss aversion with respect to cost. In general, we observe diminishing sensitivity with respect to gains and losses in both time and cost dimensions.

We find significant probability weighting, in the sense that allowing for probability weighting turns out to be a significant improvement of the explanatory power of the behavioural model, compared to a model without probability weighting. It is difficult to ascertain the economic significance of the probability weighting, since there are considerable differences in the shape of the estimated weighting functions when we apply the functional form from Tversky and Kahneman (1992) compared to the functional form from Prelec (1998): For the former, the deviation from linearity (corresponding to neutral weighting) is small, while for the Prelec-type weighting functions, the deviation is substantial.

According to Wakker (2010), the most common finding, for both gains and losses, is an inverse S-shaped weighting function, which overweights low ranks and underweights high ranks. This is the pattern we find when applying the single-parameter functional form from Prelec (1998) and the functional form from Tversky and Kahneman (1992), though not when considering gains separately. Applying the more flexible forms from Prelec (1998) results in concave weighting functions. A common result, however, is that low ranks are overweighted for losses. In the cumulative prospect theory model, this is equivalent to overweighting the outcome that yields the largest loss. When assuming a common weighting function for gains and losses, we also find that low ranks are overweighted, equivalent to overweighting all extreme outcomes (largest gain, smallest gain, smallest loss, and largest loss).

References

Avineri, E., Bovy, P., 2008. Parameter identification of prospect theory model for travel choice analysis. Transportation Research Record 2082, 141–147. [98]

Avineri, E., Prashker, J. N., 2004. Violations of expected utility theory in route-choice stated preferences: Certainty effect and inflation of small probabilities. Transportation Research Record 1894, 222–229. [97]

Bates, J., Polak, J., Jones, P., Cook, A., 2001. The valuation of reliability for personal travel. Transportation Research, Part E 37, 191–229. [96, 97]

Booij, A., van Praag, B., van de Kuilen, G., 2010. A parametric analysis of prospect theory's functionals for the general population. Theory and Decision 68, 115–148. [104, 105]

Brownstone, D., Small, K., 2005. Valuing time and reliability: assessing the evidence from road pricing demonstrations. Transportation Research, Part A 39, 279–293. [96]

de Jong, G., Tseng, Y., Kouwenhoven, M., Verhoef, E., Bates, J., 2007. The value of travel time and travel time reliability: Survey design. Final report. Report to The Netherlands Ministry of Transport, Public Works and Water Management. [96]

de Lapparent, M., Ben-Akiva, M., 2011. Risk aversion in travel mode choice model with rank dependent utility. Forthcoming in Mathematical Population Studies. [98]

de Palma, A., Picard, N., 2005. Route choice under travel time uncertainty. Transportation Research Part A 39, 295–324. [95]

de Palma, A., Picard, N., 2006. Equilibria and information provision in risky networks with risk-averse drivers. Transportation Science 40, 393–408. [95]

Doornik, J. A., 2001. Ox: An Object-Oriented Matrix Language. Timberlake Consultants Press London. [103]

Fosgerau, M., Engelson, L., 2011. The value of travel time variance. Transportation Research, Part B 45, 1–8. [96, 99]

Fosgerau, M., Hjorth, K., Brems, C., Fukuda, D., 2008. Travel time variability: Definition and valuation. DTU Transport, Report to The Danish Ministry of Transport. [96]

Fosgerau, M., Karlström, A., 2010. The value of reliability. Transportation Research. Part B: Methodological 44, 38 – 49. [99]

Harless, D., Camerer, C., 1994. The predictive utility of generalized expected utility theories. Econometrica 62, 1251–1289. [97]

Harrison, G., Cox, J., 2008. Risk aversion in Experiments. Vol. 12 of Research in Experimental Economics. Emerald Group. [97]

Harrison, G., Rutström, E., 2009. Expected utility theory and prospect theory: one wedding and a decent funeral. Experimental Economics 12, 133–158. [97]

Hensher, D. A., Li, Z., 2011. Valuing travel time variability within a rank-dependent utility framework and an investigation of unobserved taste heterogeneity, forthcoming in Journal of Transport Economics and Policy. [98]

Hensher, D. A., Li, Z., Rose, J. M., 2011. Accommodating risk in the valuation of expected travel time savings, forthcoming in Journal of advanced transportation. [96, 98]

Hey, J., Orme, C., 1994. Investigating generalizations of expected utility theory using experimental data. Econometrica 62, 1291–1326. [97]

Hollander, Y., 2006. Direct versus indirect models for the effects of unreliability. Transportation Research, Part A 40, 699–711. [96]

Kahneman, D., Tversky, A., 1979. Prospect theory: An analysis of decision under risk. Econometrica 47, 263–291. [97]

Köszegi, B., Rabin, M., 2007. Reference-dependent risk attitudes. American Economic Review 97, 1047–1073. [97]

Lam, T., Small, K., 2001. The value of time and reliability: measurement from a value pricing experiment. Transportation Research, Part E 37, 231–251. [96]

Loomes, G., Moffatt, P., Sugden, R., 2002. A microeconometric test of alternative stochastic theories of risky choice. Journal of Risk and Uncertainty 24, 103–130. [97]

Michea, A., Polak, J., 2006. Modelling risky choice behaviour: Evaluating alternatives to expected utility theory. 11th International Conference on Travel Behaviour Research, Kyoto, Japan. [98]

Noland, R. B., Polak, J., 2002. Travel time variability: a review of theoretical and empirical issues. Transport Reviews 22, 39–54. [96]

Noland, R. B., Small, K., 1995. Travel-time uncertainty, departure time choice, and the cost of morning commutes. Transportation Research Record 1493, 150–158. [96]

Noland, R. B., Small, K., Koskenoja, P., Chu, X., 1998. Simulating travel reliability. Regional science and urban economics 28, 535–564. [96]

Prelec, D., 1998. The probability weighting function. Econometrica 66, 497–527. [102, 106]

Quiggin, J., 1982. A theory of anticipated utility. Journal of Economic Behavior and Organization 3, 225–243. [97]

Ramjerdi, F., Flügel, S., Samstad, H., Killi, M., 2010. Den norske verdsettingsstudien, Tid. Report for the Norwegian Ministry of Transport, Institute of Transport Economics, Oslo, Report no. 1053B/2010. [96, 101]

Rietveld, P., Bruinsma, F., van Vuuren, D., 2001. Coping with unreliability in public transport chains: A case study for netherlands. Transportation Research Part A 35, 539–559. [96]

Samstad, H., Ramjerdi, F., Veisten, K., Navrud, S., Magnussen, K., Flügel, S., Killi, M., Halse, A. H., Elvik, R., Martin, O. S., 2010. Den norske verdsettingsstudien, Sammendragsrapport. Report for the Norwegian Ministry of Transport, Institute of Transport Economics, Oslo, Report no. 1053/2010. [101]

Small, K., 1982. The scheduling of consumer activities: Work trips. The American Economic Review 72, 467–479. [96]

Small, K., Noland, R., Chu, X., Lewis, D., 1999. Valuation of travel-time savings and predictability in congested conditions for highway user-cost estimation. National Cooperative Highway Research Program, Transportation Research Board, Report 431. [96]

Small, K., Winston, C., Yan, J., 2005. Uncovering the distribution of motorists' preferences for travel time and reliability. Econometrica 73, 1367–1382. [96]

Stott, H., 2006. Cumulative prospect theory's functional menagerie. Journal of Risk and Uncertainty 32, 101–130. [97, 100]

Timmermans, H., 2010. On the (ir)relevance of prospect theory in modelling uncertainty in travel decisions. European Journal of Transport and Infrastructure Research 10, 368–384. [98]

Tseng, Y.-Y., Verhoef, E. T., 2008. Value of time by time of day: A stated-preference study. Transportation Research Part B: Methodological 42, 607–618. [96]

Tversky, A., Kahneman, D., 1992. Advances in prospect theory: Cumulative representation of uncertainty. Journal of Risk and Uncertainty 5, 297–323. [97, 99, 100, 102, 105, 106]

Vickrey, W. S., 1969. Congestion theory and transport investment. The American Economic Review 59, 251–260. [96]

Vickrey, W. S., 1973. Pricing, metering, and efficiently using urban transportation facilities. Highway Research Record 476, 36 – 48. [96]

Wakker, P., 2010. Prospect theory for risk and ambiguity. Cambridge University Press. [100, 104, 106]

Appendix

Table 5.2: Summary statistics of the sample.

	Car short	PT short	Car long	PT long	Air
Sample size					
- individuals	1531	183	543	918	735
- obs	9186	1098	3258	5508	4410
Reference travel time					
- min	10.0	10.0	60.0	60.0	80.0
- mean	25.1	28.5	183.5	251.2	189.6
- max	90.0	90.0	810.0	900.0	600.0
Reference cost					
- min	8.0	10.0	70.0	50.0	150.0
- mean	46.8	32.4	429.6	302.0	1187.2
- max	245.0	92.0	1464.0	1500.0	5000.0
Travel time attributes					
- min	-38.0	-36.0	-275.0	-338.0	-197.0
- mean	2.0	2.5	12.0	19.8	14.6
- max	97.0	97.0	684.0	990.0	554.0
Travel time attributes (gains)					
- min	-38.0	-36.0	-275.0	-338.0	-197.0
- mean	-5.0	-4.9	-29.5	-37.9	-30.1
- max	-1.0	-1.0	-1.0	-1.0	-1.0
Travel time attributes (losses)					
- min	1.0	1.0	1.0	1.0	1.0
- mean	8.8	9.8	54.9	75.6	58.2
- max	97.0	97.0	684.0	990.0	554.0
Cost attributes					
- min	-73.0	-23.0	-483.0	-750.0	-1000.0
- mean	-1.2	-0.5	-1.7	-2.0	-7.6
- max	74.0	14.0	468.0	750.0	750.0
Cost attributes (gains)					
- min	-73.0	-23.0	-483.0	-750.0	-1000.0
- mean	-12.3	-6.4	-69.0	-57.5	-155.8
- max	-1.0	-1.0	-8.0	-6.0	-12.0
Cost attributes (losses)					
- min	1.0	1.0	6.0	4.0	8.0
- mean	7.6	4.8	61.2	49.2	125.9
- max	74.0	14.0	468.0	750.0	750.0
Choice variable (y)					
- min	1.0	1.0	1.0	1.0	1.0
- mean	1.5	1.5	1.5	1.5	1.5
- max	2.0	2.0	2.0	2.0	2.0

Table 5.3: Distribution of gain and loss outcomes on $(p+r,r)$.

	Car short		PT short		Car long		PT long		Air	
$(p+r,r)$	Gains	Losses	Gains	Losses	Gains	Losses	Gains	Losses	Gains	Losses
$(0.2,0)$	15080	17189	1822	2068	6008	6252	9717	10546	7664	8447
$(0.4,0)$	167		17							
$(0.4,0.2)$	10747	12417	1303	1503	4255	4834	6664	8132	5312	6161
$(0.6,0.4)$	3832	3076	463	384	1347	1117	2267	1847	1831	1502
$(0.8,0)$	102		9							
$(0.8,0.2)$	663	1513	80	162	277	517	479	915	371	706
$(0.8,0.6)$	1115	2414	102	311	34	548	66	1581	301	1314
$(1,0.8)$	695	2190	72	288	233	380	445	1235	373	1151
Totals	32401	38799	3868	4716	12154	13648	19638	24256	15852	19281

Table 5.4: Estimation results, NoW models (parameter estimates and standard errors).

	Car short			PT short			Car long			PT long			Air		
Parameter	Est	SE		Est	SE		Est	SE		Est	SE		Est	SE	
β_c^+	1.00			1.00			1.00			1.00			1.00		
β_c^-	0.89	0.04	***	0.76	0.12	***	1.07	0.10	***	1.01	0.10	***	0.91	0.06	***
β_t^+	0.32	0.03	***	0.04	0.05		0.60	0.17	***	0.18	0.05	***	0.26	0.06	***
β_t^-	0.84	0.07	***	0.48	0.15	***	1.58	0.45	***	0.95	0.22	***	0.46	0.11	***
α_c	0.39	0.02	***	0.15	0.14		0.64	0.05	***	0.55	0.05	***	0.42	0.04	***
α_t	0.79	0.03	***	0.81	0.07	***	0.88	0.04	***	0.89	0.03	***	0.94	0.03	***
μ	0.59	0.04	***	0.85	0.22	***	0.06	0.02	***	0.07	0.02	***	0.16	0.03	***
Log likelihood value	-4904.89			-629.83			-1891.81			-3195.02			-2316.23		
Number of parameters	6			6			6			6			6		
Adj. ρ^2	0.23			0.16			0.16			0.16			0.24		

***, ** and * indicate significance at the 1, 5 and 10 percent level, respectively.

Table 5.5: Estimation results, TK1 models (parameter estimates and standard errors).

	Car short			PT short			Car long			PT long			Air		
Parameter	Est	SE		Est	SE		Est	SE		Est	SE		Est	SE	
β_c^+	1.00			1.00			1.00			1.00			1.00		
β_c^-	0.90	0.04	***	0.77	0.12	***	1.07	0.10	***	1.02	0.09	***	0.91	0.06	***
β_t^+	0.32	0.03	***	0.06	0.05		0.72	0.21	***	0.28	0.07	***	0.31	0.07	***
β_t^-	0.87	0.07	***	0.51	0.16	***	1.67	0.47	***	1.12	0.25	***	0.49	0.12	***
α_c	0.39	0.02	***	0.15	0.13		0.63	0.05	***	0.54	0.04	***	0.41	0.04	***
α_t	0.79	0.03	***	0.80	0.07	***	0.87	0.04	***	0.86	0.03	***	0.92	0.03	***
γ	0.75	0.03	***	0.73	0.08	***	0.76	0.08	***	0.67	0.03	***	0.72	0.06	***
μ	0.60	0.04	***	0.86	0.22	***	0.06	0.02	***	0.08	0.02	***	0.16	0.03	***
Log likelihood value	-4884.55			-625.63			-1888.22			-3164.82			-2308.15		
Number of parameters	7			7			7			7			7		
Adj. ρ^2	0.23			0.17			0.16			0.17			0.24		

***, ** and * indicate significance at the 1, 5 and 10 percent level, respectively.

Table 5.6: Estimation results, TK2 models (parameter estimates and standard errors).

	Car short			PT short			Car long			PT long			Air		
Parameter	Est	SE		Est	SE		Est	SE		Est	SE		Est	SE	
β_c^+	1.00			1.00			1.00			1.00			1.00		
β_c^-	0.90	0.04	***	0.80	0.11	***	1.08	0.10	***	1.04	0.09	***	0.91	0.06	***
β_t^+	0.60	0.06	***	0.55	0.21	***	0.96	0.29	***	1.17	0.29	***	0.44	0.11	***
β_t^-	0.84	0.07	***	0.44	0.14	***	1.77	0.48	***	1.17	0.25	***	0.57	0.14	***
α_c	0.38	0.02	***	0.16	0.13		0.62	0.05	***	0.53	0.04	***	0.40	0.04	***
α_t	0.77	0.02	***	0.82	0.07	***	0.83	0.04	***	0.82	0.02	***	0.87	0.03	***
γ^+	2.98	0.25	***	6.25	1.71	***	1.75	0.36	***	3.75	0.33	***	2.09	0.32	***
γ^-	0.80	0.04	***	0.76	0.09	***	0.77	0.09	***	0.67	0.04	***	0.82	0.09	***
μ	0.64	0.04	***	0.89	0.22	***	0.07	0.02	***	0.09	0.02	***	0.18	0.04	***
Log likelihood value	-4823.54			-616.56			-1883.09			-3119.99			-2295.93		
Number of parameters	8			8			8			8			8		
Adj. ρ^2	0.24			0.18			0.16			0.18			0.25		

***, ** and * indicate significance at the 1, 5 and 10 percent level, respectively.

Table 5.7: Estimation results, Prl1 models (parameter estimates and standard errors).

	Car short			PT short			Car long			PT long		Air		
Parameter	Est	SE		Est	SE		Est	SE		Est	SE	Est	SE	
β_c^+	1.00			1.00			1.00					1.00		
β_c^-	0.90	0.04	***	0.78	0.12	***	1.07	0.10	***	Convergence		0.91	0.06	***
β_t^+	0.36	0.04	***	0.12	0.07		0.85	0.26	***	problems		0.37	0.09	***
β_t^-	0.87	0.07	***	0.53	0.17	***	1.69	0.47	***			0.48	0.12	***
α_c	0.40	0.02	***	0.16	0.13		0.64	0.05	***			0.41	0.04	***
α_t	0.83	0.02	***	0.81	0.06	***	0.88	0.04	***			0.93	0.03	***
θ	0.31	0.08	***	0.13	0.20		0.47	0.19	**			0.35	0.13	***
μ	0.58	0.04	***	0.85	0.22	***	0.06	0.02	***			0.16	0.03	***
Log likelihood value	-4882.42			-623.32			-1888.87					-2307.23		
Number of parameters	7			7			7					7		
Adj. ρ^2	0.23			0.17			0.16					0.24		

***, ** and * indicate significance at the 1, 5 and 10 percent level, respectively.

Table 5.8: Estimation results, Prl2 models (parameter estimates and standard errors).

	Car short			PT short			Car long			PT long		Air		
Parameter	Est	SE		Est	SE		Est	SE		Est	SE	Est	SE	
β_c^+	1.00			1.00			1.00					1.00		
β_c^-	0.88	0.03	***	0.79	0.10	***	1.09	0.10	***	Convergence		0.91	0.06	***
β_t^+	0.33	0.03	***	0.12	0.06	**	0.76	0.21	***	problems		0.43	0.10	***
β_t^-	0.83	0.07	***	0.55	0.17	***	1.44	0.39	***			0.72	0.18	***
α_c	0.35	0.02	***	0.13	0.12		0.58	0.05	***			0.39	0.04	***
α_t	0.61	0.02	***	0.59	0.06	***	0.75	0.04	***			0.73	0.04	***
η	0.19	0.05	***	0.14	0.14		0.34	0.15	**			0.38	0.10	***
θ	2.54	0.61	***	2.09	1.99		1.72	1.07				1.33	0.63	**
μ	0.73	0.04	***	1.04	0.23	***	0.08	0.02	***			0.19	0.04	***
Log likelihood value	-4767.87			-603.10			-1876.26					-2289.16		
Number of parameters	8			8			8					8		
Adj. ρ^2	0.25			0.20			0.17					0.25		

***, ** and * indicate significance at the 1, 5 and 10 percent level, respectively.

Table 5.9: Estimation results, Prl3 models (parameter estimates and standard errors).

	Car short			PT short			Car long			PT long			Air		
Parameter	Est	SE		Est	SE		Est	SE		Est	SE		Est	SE	
β_c^+	1.00			1.00			1.00			1.00			1.00		
β_c^-	0.88	0.03	***	0.79	0.10	***	1.09	0.10	***	1.04	0.09	***	0.91	0.06	***
β_t^+	0.37	0.04	***	0.12	0.06	**	0.79	0.24	***	0.92	0.23	***	0.47	0.11	***
β_t^-	0.87	0.07	***	0.55	0.17	***	1.47	0.41	***	1.44	0.31	***	0.70	0.18	***
α_c	0.35	0.02	***	0.13	0.12		0.58	0.05	***	0.47	0.04	***	0.39	0.04	***
α_t	0.62	0.02	***	0.59	0.06	***	0.75	0.04	***	0.63	0.03	***	0.76	0.04	***
η^+	0.81	0.31	***	0.13	0.52		0.44	0.38		0.88	0.43	**	0.92	0.44	**
η^-	0.35	0.07	***	0.14	0.18		0.38	0.18	**	0.21	0.10	**	0.55	0.12	***
θ	1.84	0.33	***	2.11	2.29		1.65	0.88	*	1.12	0.39	***	1.27	0.42	***
μ	0.73	0.04	***	1.04	0.23	***	0.08	0.02	***	0.12	0.02	***	0.19	0.04	***
Log likelihood value	-4764.17			-603.10			-1876.22			-3066.70			-2287.88		
Number of parameters	9			9			9			9			9		
Adj. ρ^2	0.25			0.20			0.17			0.19			0.25		

***, ** and * indicate significance at the 1, 5 and 10 percent level, respectively.

Table 5.10: Likelihood ratio tests (p-values)

	p-values				
	Car short	PT short	Car long	PT long	Air
Hypothesis: $\beta_t^+ = \beta_t^-$					
NoW	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
TK1	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
TK2	< 0.01	0.51	< 0.01	0.99	0.06
Prl1	< 0.01	0.02			0.02
Prl2	< 0.01	< 0.01	< 0.01		< 0.01
Prl3	< 0.01		0.02	0.02	0.03
Hypothesis: $\beta_c^+ = \beta_c^-$					
NoW	< 0.01	0.07	0.49	0.91	0.14
TK1	< 0.01	0.08	0.46	0.86	0.14
TK2	< 0.01	0.11	0.40	0.69	0.14
Prl1	0.01	0.10	0.45		0.14
Prl2	< 0.01	0.07	0.35		0.14
Prl3	< 0.01	0.07	0.35	0.65	0.15
Hypothesis: No weighting					
TK1	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
TK2	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
Prl1	< 0.01	< 0.01	0.02		< 0.01
Prl2	< 0.01	< 0.01	< 0.01		< 0.01
Prl3	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01

Table 5.11: Estimated ratios β_t^- / β_t^+.

	Car short		PT short		Car long		PT long		Air	
NoW	2.7	***	10.9	***	2.7	***	5.1	***	1.8	***
TK1	2.8	***	9.2	***	2.3	***	4.0	***	1.6	***
TK2	1.4	***	0.8		1.8	***	1.0		1.3	*
Prl1	2.4	***	4.4	**	2.0	(nc)			1.3	**
Prl2	2.5	***	4.5	***	1.9	***			1.7	***
Prl3	2.3	***	4.5	(nc)	1.9	**	1.6	**	1.5	**

*** denotes that β_t^- and β_t^+ are significantly different at the 1% level, ** at the 5% level, and * at the 10% level (LR tests). (nc) denotes that the LR test could not be performed because the restricted model did not converge to an optimal solution.

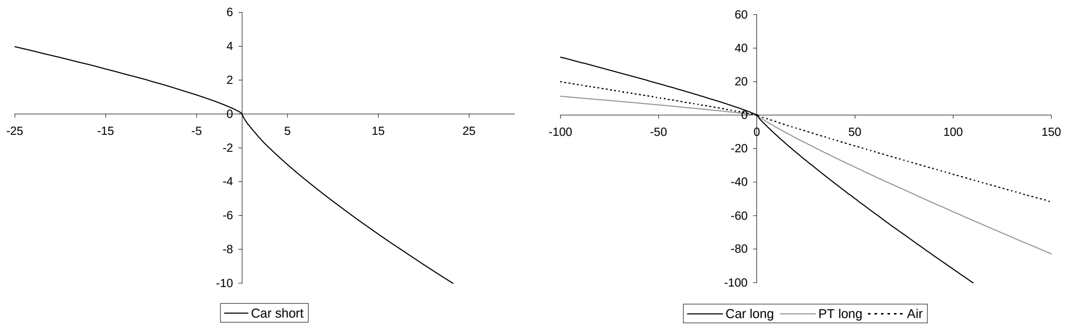

Figure 5.3: Value functions for time, NoW models (negative values are gains, positive values are losses)

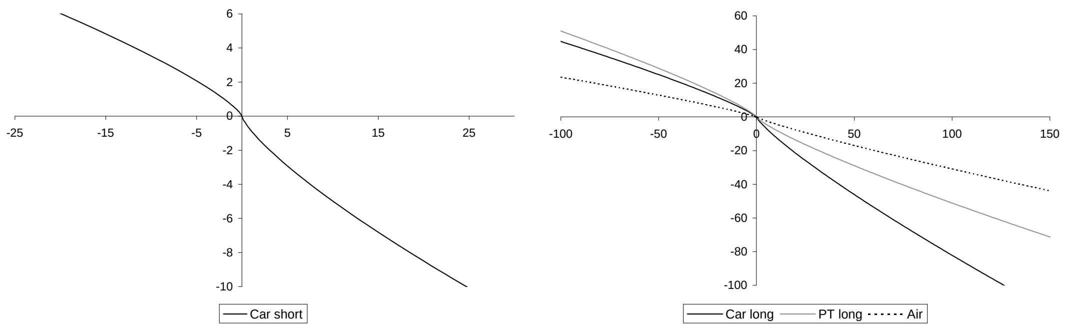

Figure 5.4: Value functions for time, TK2 models (negative values are gains, positive values are losses)

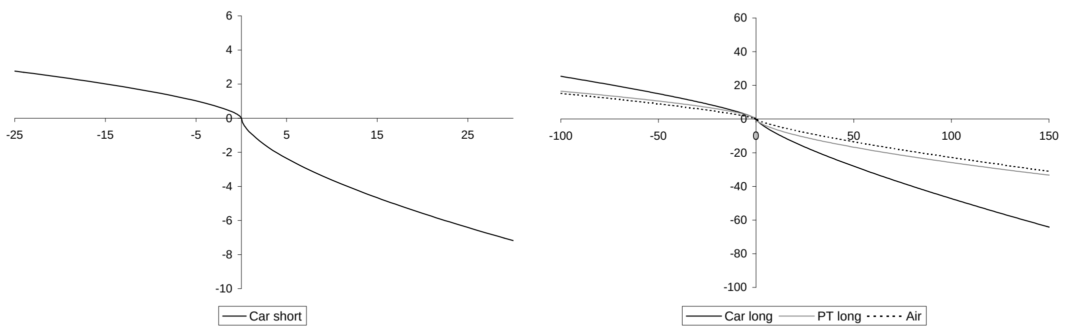

Figure 5.5: Value functions for time, Prl3 models (negative values are gains, positive values are losses)

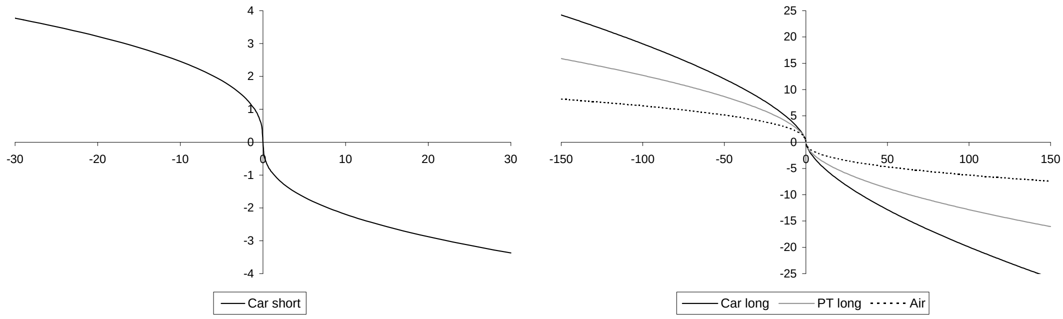

Figure 5.6: Value functions for cost, NoW models (negative values are gains, positive values are losses)

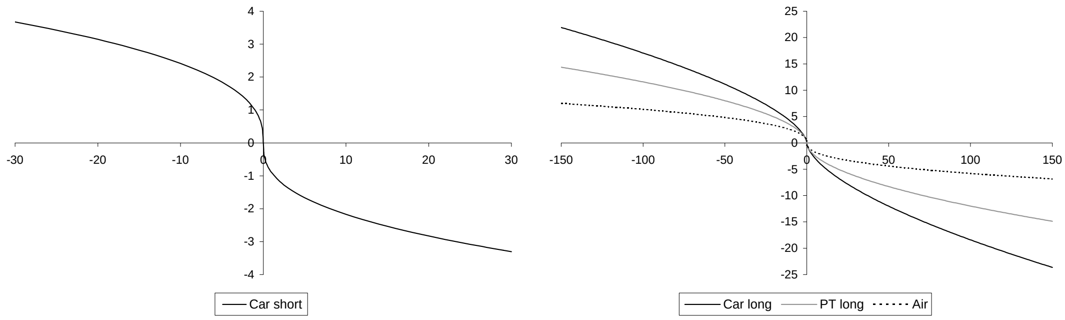

Figure 5.7: Value functions for cost, TK2 models (negative values are gains, positive values are losses)

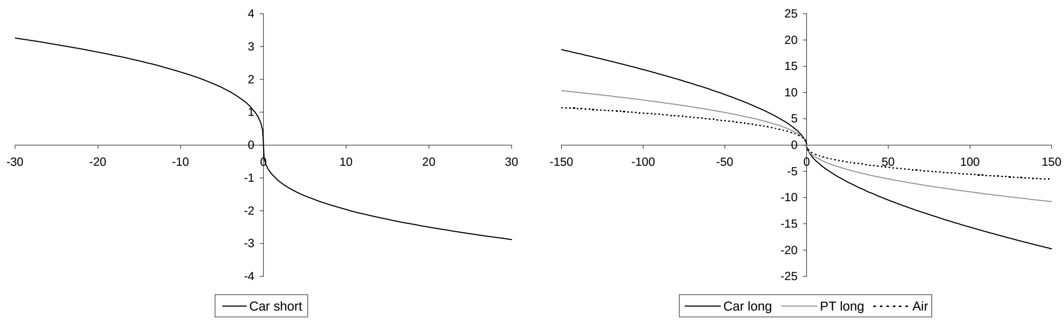

Figure 5.8: Value functions for cost, Prl3 models (negative values are gains, positive values are losses)

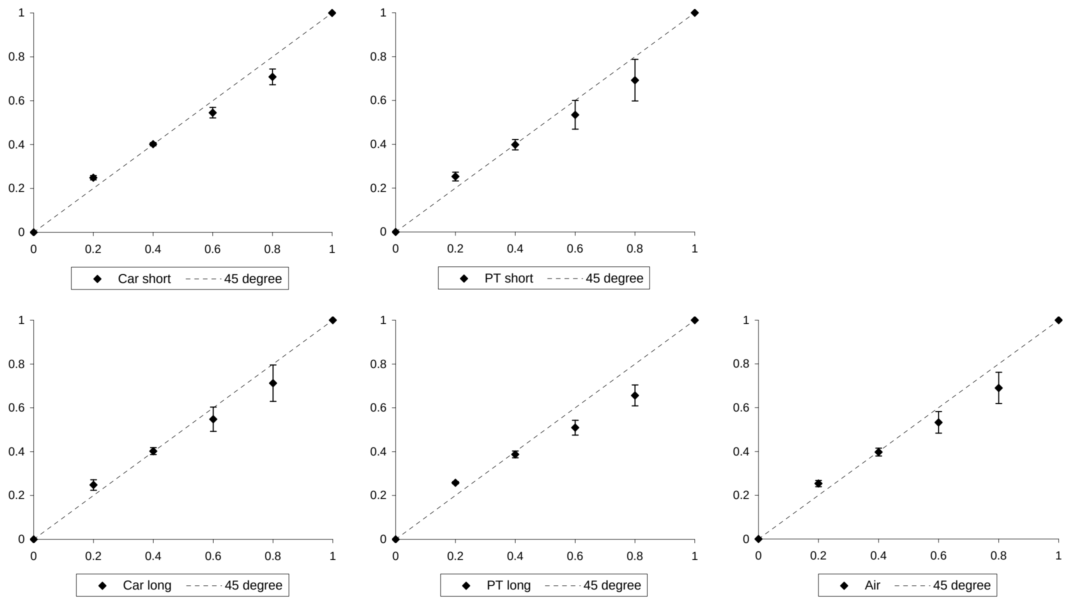

Figure 5.9: Weighting functions with 95% confidence limits, TK1 models. Confidence limits are computed using the Delta method.

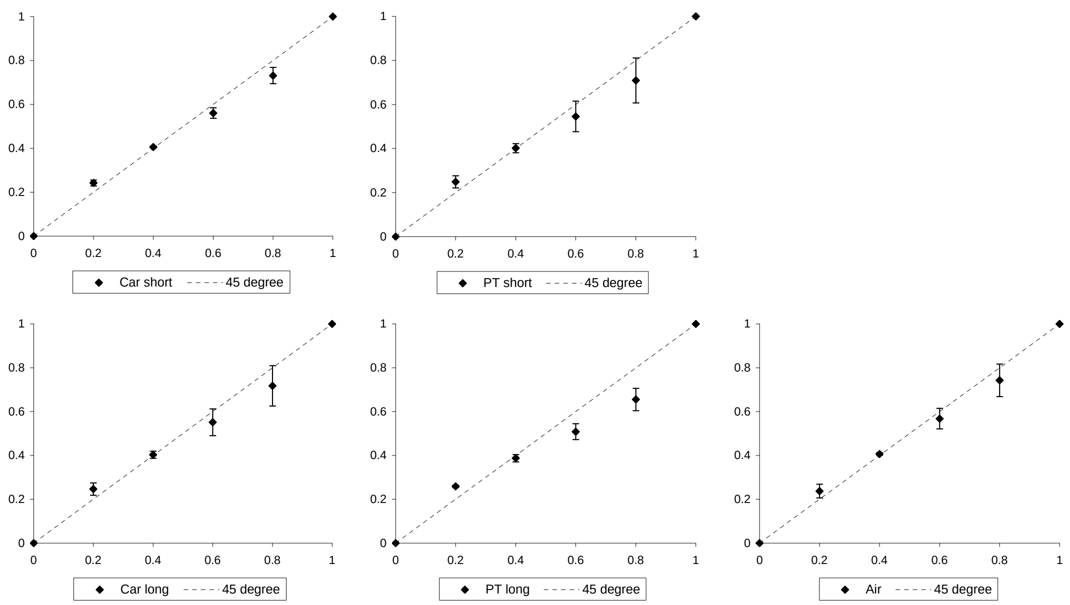

Figure 5.10: Weighting functions for losses with 95% confidence limits, TK2 models. Confidence limits are computed using the Delta method.

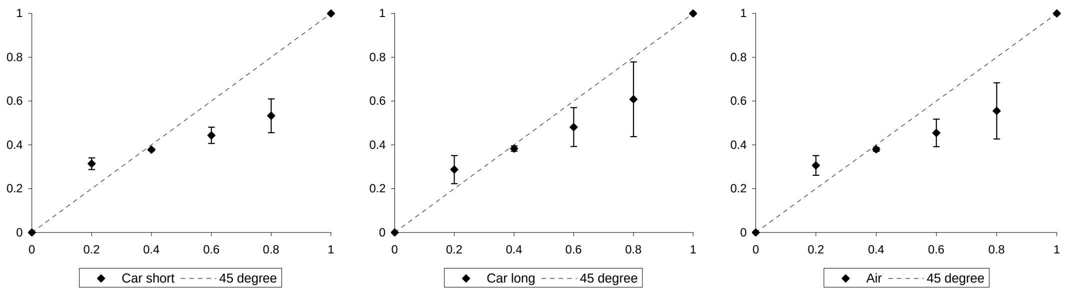

Figure 5.11: Weighting functions with 95% confidence limits, Prl1 models. Confidence limits are computed using the Delta method.

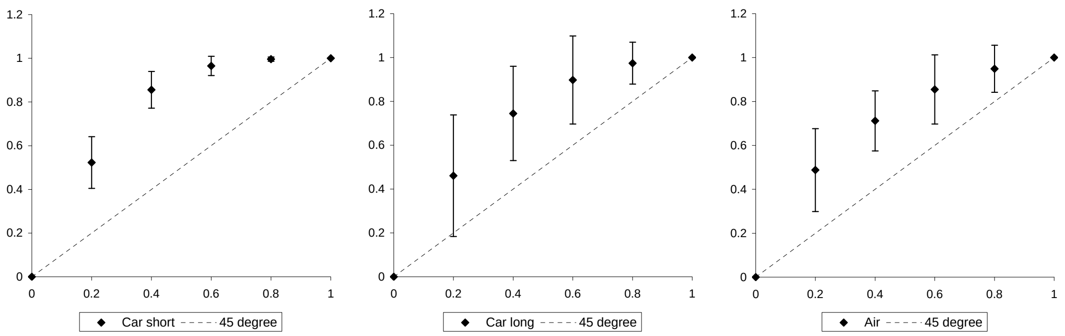

Figure 5.12: Weighting functions with 95% confidence limits, Prl2 models. Confidence limits are computed using the Delta method.

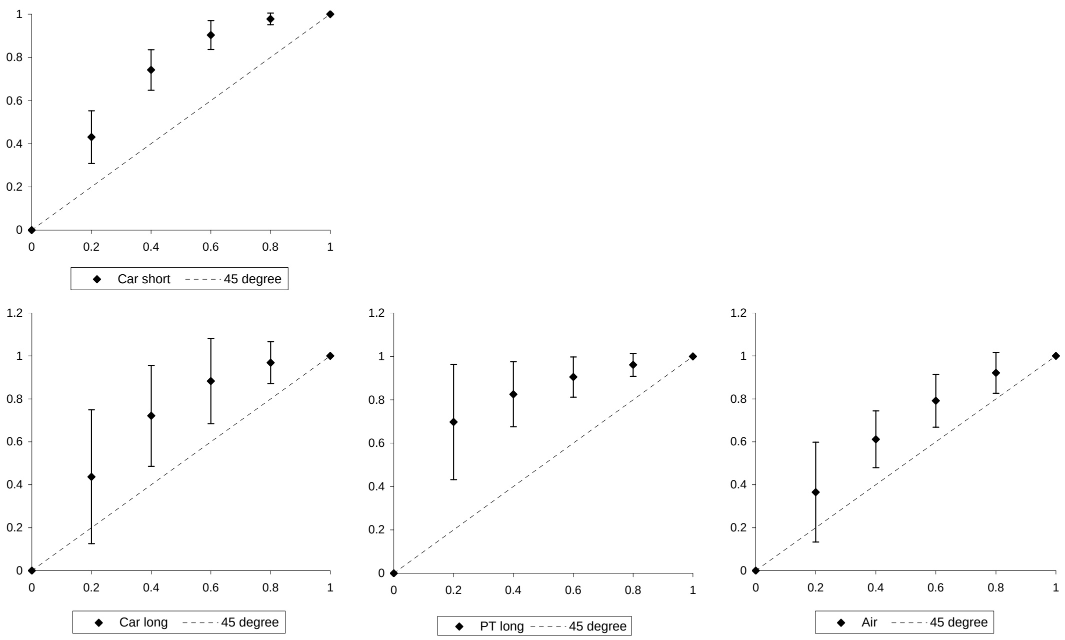

Figure 5.13: Weighting functions for losses with 95% confidence limits, Prl3 models. Confidence limits are computed using the Delta method.

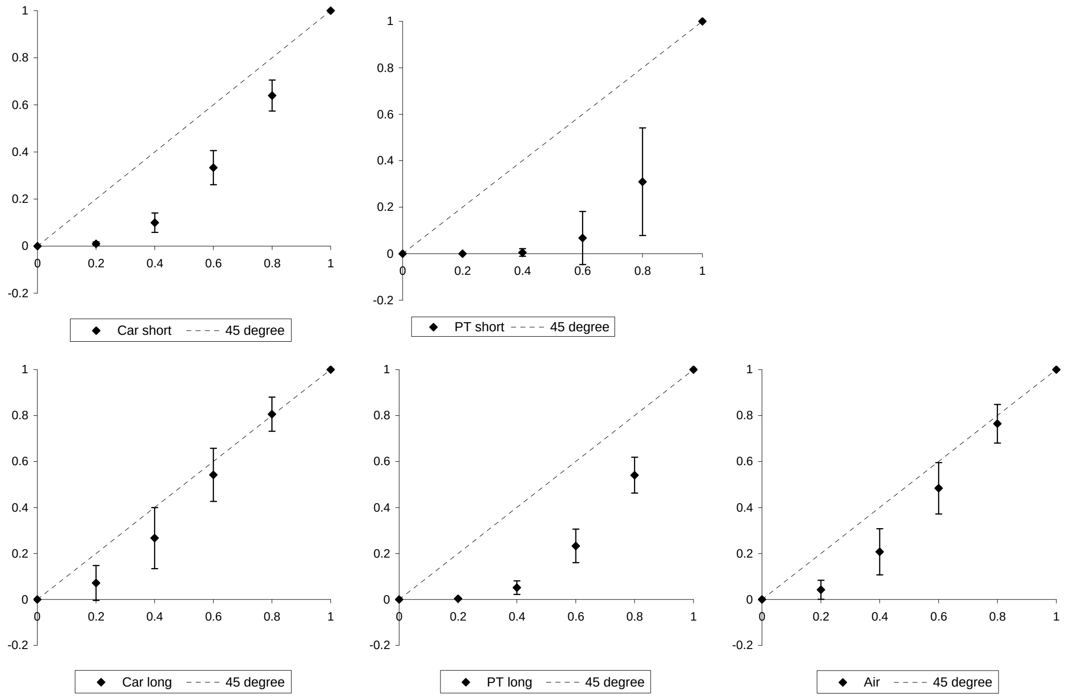

Figure 5.14: Weighting functions for gains with 95% confidence limits, TK2 models. Confidence limits are computed using the Delta method.

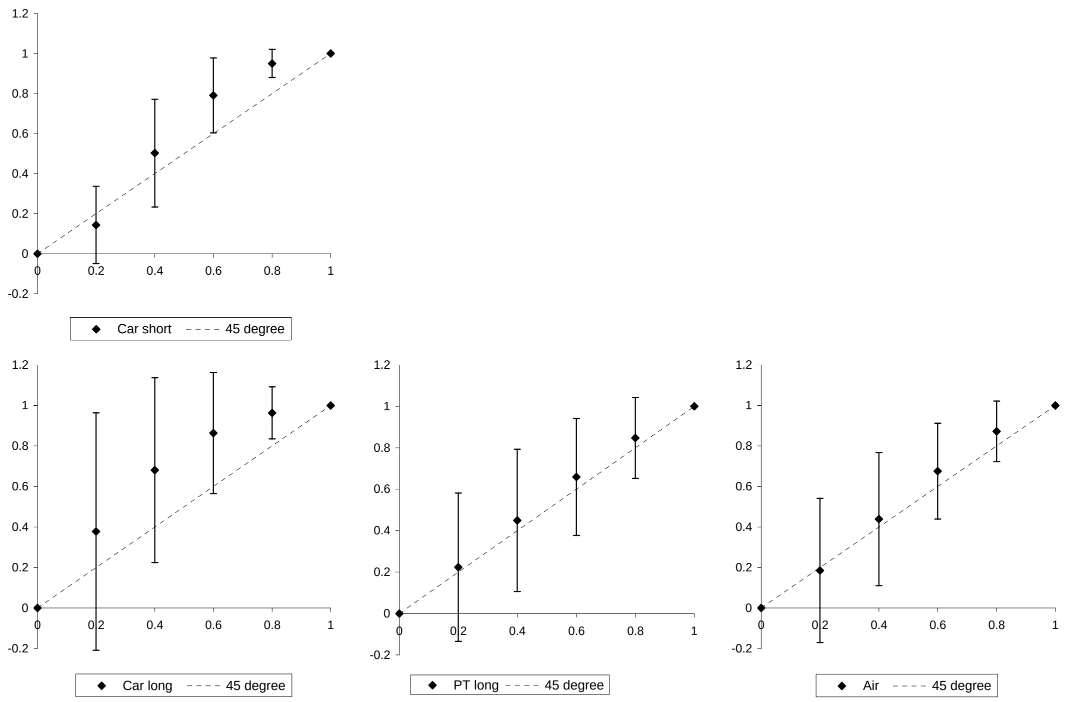

Figure 5.15: Weighting functions for gains with 95% confidence limits, Prl3 models. Confidence limits are computed using the Delta method.