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USING STATE-OF-THE-ART MODELS IN APPLIED WORK: TRAVELLERS WILLINGNESS TO PAY FOR A TOLL TUNNEL IN COPENHAGEN

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Highlights:

- Demonstration of effectiveness of advanced choice modelling in practical forecasting context.
- Evidence that the design of stated choice surveys impacts the resulting values of time (VTT).
- No significant difference in VTT observed between intercept and online panel respondents.
- Substantial random variation in VTTs for commute and other travel, in addition to socio-demographic and design effects.
- Importance of correlation between time period and route choice alternatives.

Abstract: Advanced model specifications for value of travel time (VTT) research have become the norm in academic studies as well as large scale national and regional studies. However, studies with a quick turnaround and also those that need to produce results suitable for implementation in existing forecasting systems often still rely on simpler approaches. This paper describes how state-of-the-art specifications can benefit such studies. We focus on the willingness of car and light van travellers in the Copenhagen area to pay to use a proposed new route which includes the new Harbour Tunnel (Havnetunnel) and completes the Copenhagen Eastern Ring Road. We adopt the very general framework from the most recent UK VTT study (Hess et al, 2017), and extend it to capture the correlation among different alternatives in the choice presentations (which reflected both route choice and time of day choice). We find extensive heterogeneity across travellers, both deterministic and random. A sample enumeration procedure was then set up to calculate average VTT values for use in forecasting demand and appraising the new Ring Road investment.

Key words: Value of travel time (VTT), Stated Choice (SC) experiment, multiplicative error structure, reference dependence, elasticities, random heterogeneity, correlation among alternatives, prototypical sampling

1. INTRODUCTION

There is substantial research and literature in quantifying travellers' values of travel time (VTT) because of its significant role in infrastructure appraisal. VTT is the monetary valuation of a one minute saving - or travellers' willingness to be compensated for a one minute increase - in their travel time. Previous evidence has found that VTT varies by travellers' journey purposes, journey length and their socio-economic characteristics, for example income, gender and age. Often VTT is given as an average, for example for cost-benefit analysis. However, research shows unambiguously that however much segmentation is incorporated in VTT models, there remains a considerable degree of variation in travellers' VTT in the population. Some people are, or think they are, more pressed for time than others, for reasons that cannot be explained through exogenous variables. This 'taste variation' is an important component of any explanation of behaviour.

VTT research covers both large-scale national studies and more focussed local applications. While the former are aimed at producing national VTT measures for use in a variety of appraisal contexts, the latter focus on very specific application contexts, often the case for the proposed construction of new tolled infrastructure (or the introduction of tolls on existing infrastructure) (e.g. Hensher et al., 1988; Ortúzar et al., 2000; Hensher, 2001; Greene and Hensher, 2003; Li and Hensher, 2012). In recent years, extensive development of the analytical toolkit for VTT work has taken place, but the focus of this has almost entirely been on large national studies (see e.g. Fosgerau et al., 2007; Hess et al., 2017).

Shorter-term studies looking at local issues are often short of budget and time and rely on less advanced modelling approaches. This is partly because the more advanced discrete choice models tend to be more complex to implement, because of the more complex model formulation (such as, some of them have no closed-form expression), and so numerical or sampling methods are required to be used to find approximate solutions. This is potentially detrimental to the reliability of the policy and infrastructure decisions that are made in such cases and also reduces the transfer of ideas from large studies to more local applications. Given the risks and the potential for large financial losses if they fail, it has become increasingly important that the outputs of SC models, such as the value of travel time savings (VTTS), be both reliable and give unbiased estimates of the true population behavioural parameters. The present paper looks in particular at a localised application and demonstrates how advanced approaches can be of benefit in such studies. The paper also addresses a number of key issues arising in the context of toll studies, namely strategic bias as well as issues with having to rely on online sampling of respondents.

The context of the present paper is a study commissioned by the Danish Road Directorate (Vejdirektoratet) to quantify the willingness of car and light van drivers and passengers in the Copenhagen area to pay to use a proposed Eastern Ring Road, the first Danish tolled road (other than bridges), involving an investment of DKK 35 billion[1], to be completed in 2035. The Eastern Ring road would be an alternative to the existing four bridges between Sjælland and Amager islands. All the existing links are congested, which is especially problematic for commuting car traffic. The two city bridges, Langebro and Knippelsbro, also need substantial repair in the near future, which puts more pressure on the city council to approve the new ring road.

The crucial issue in predicting whether drivers will choose to pay the toll, rather than use the existing congested bridges, is to understand the VTT of drivers and passengers. The current estimate of traveller VTT in Copenhagen dates back to data collected in 2004, in the first Danish national VVT project, DATIV (Tetraplan, 2005). The key objective of the current study was to provide up-to-date evidence of the willingness of car and light van travellers to pay to use the proposed new tunnel route.

Further, the nature of forecasting demand for tolled facilities focusses attention on travellers with high values of time. Thus it is important to know the fraction of travellers whose value of time exceeds the critical value[2], which will vary with the toll and detailed design of the project, specifically in terms of how much time is saved and by whom. For these two reasons it is necessary to understand and quantify the distribution of the value of travel time among drivers and passengers. To quantify travellers' VTT, a stated choice (SC) survey was undertaken with drivers and passengers who made journeys by car or van on a weekday across the harbour in Copenhagen. State-of-the-art discrete choice models were developed from the SC data, including incorporation of a multiplicative error specification, explicit testing of reference dependence (De Borger and Fosgerau, 2008; Hess et al., 2017), direct estimation of time, cost, distance and income elasticities and representation of deterministic and random heterogeneity. Specifically, we adopted the modelling framework used in the UK Value of time study (Hess et al, 2017) and extended it to capture correlation among different route and timing alternatives in the four-alternative presentations.

We contribute to the empirical literature on VTT in policy testing in three ways. First, we deploy state-of-the-art discrete choice modelling techniques to calculate travellers' values of time in a localised setting. Second, this study provides further evidence on factors that influence travellers' VTT, including socio-economic, trip characteristics and study design variables, where we also focus on the impact of sampling and potential strategic bias and tunnel phobia. Third, the findings from the study are incorporated in an operational traffic model for Greater Copenhagen, the Ørestad Traffic Model (OTM) model, to develop new forecasts of future travel demand for the new Ring Road. For the first time in traffic modelling in Denmark, the new time values are consistently incorporated in both the demand model and assignment components of the OTM. Finally, the VTT obtained from this project are currently being incorporated in the COMPASS model (Copenhagen Model for Person Activity Scheduling and Simulations), an activity-based model for Greater Copenhagen.

The remainder of this paper is structured as follows: Section 2 describes the survey design and data collection work. This is followed in Section 3 by model specification and results in Section 4. Section 5 summarises the research undertaken and provides the recommended values of time.

2. DATA COLLECTION

This section discusses the survey design and data collection work and provides some initial summaries of the collected data.

2.1 Survey structure

Surveys were undertaken with respondents who travelled in the corridor of interest, specifically those who crossed one of the four harbour crossings between Sjælland and Amager[3] as a driver or passenger in a car or van

[1] Approximately 4.7 billion euros (1DKK = €0.13)

[2] Some drivers, e.g. those on business trips whose employers are paying their costs, may be willing to pay a toll for *any* time saving, even if it is quite small.

[3] Sjælland is the large island to the West of the harbour, containing most of the metropolitan area of Copenhagen; Amager, the smaller island to the East, contains some suburbs, the airport and leads to the connection to Sweden.

on a weekday in the month previous to the survey. The survey commenced by collecting information on a recent in-scope trip made by the respondent, including the trip origin, destination, week day of the journey, journey purpose, frequency of journey, length of journey (in minutes), departure time and flexibility, whether the journey was made in congested conditions, the perceived level of congestion, whether the respondent made the journey as a driver or passenger and the number of people travelling in the car. This was followed by the SC experiment. After the SC experiment, respondents were also asked to provide information on their socio-economic characteristics as well as answering attitudinal questions concerning congestion and travelling in tunnels.

2.2 Stated choice (SC) component

SC experiments are widely used for measuring travellers' VTT. In such experiments, respondents are asked to make choices between hypothetical travel alternatives, with varying costs and times, developed from a carefully constructed experimental design. The choices that respondents make in these experiments are used to quantify VTT and the factors that influence VTT. In the context of a hypothetical future tunnel such as in the present study, this reliance on hypothetical as opposed to real choices is essentially unavoidable but calls for great care in the design and execution of the survey work. In what follows, we look at the experimental setup in terms of alternatives and attributes, before discussing experimental design and testing.

The focus of the present study was both on route choice and the journey timing decisions. While previous studies have often looked separately at different dimensions of choice or different journey characteristics, this reliance on simple survey designs has received growing criticism of late (cf. Hess et al., 2020). With this in mind, we sought to collect all relevant behaviour effects in a single experiment where car drivers and passengers were presented with options reflecting route options (tolled and untolled routes) and departure time options (peak and off-peak). Respondents who travelled in the peak period and who reported flexibility in their departure time as well as respondents who travelled in the off-peak period but reported that their preferred departure time was in the peak period were presented with four options – a peak hour toll road option, an off-peak toll road option, a peak hour un-tolled road option and an off-peak un-tolled road option. Respondents who travelled in the peak and had no flexibility in changing their departure time were presented with two options only – a peak hour toll road option and peak hour un-tolled road option. Respondents who travelled in the off-peak period and who stated that their preferred departure time was in the off-peak were also presented two options only – an off-peak toll road option and an off-peak un-tolled road option – on the basis that they would never switch to a different time period alternative. A single experiment was designed to maximise the statistical information from the data and to avoid the likely inconsistencies in values from multiple experiments (Hess et al., 2017). In addition, presenting all options simultaneously better reflects the choices that travellers would have to make in the real world and is therefore more realistic than presenting these choices in separate experiments, i.e. a route choice experiment separate from departure time period choice.

In the experiment there was no explicit mention of the Harbour Tunnel, or Eastern Ring Road, to minimise potential political (strategic) biases. Instead respondents were presented with the choice of a hypothetical route (described as 'new tunnel' in the stated choice scenarios). Using a hypothetical route also allowed a wider range of times and costs to be tested in the experiment, which was necessary to identify the distribution of VTTs.

The travel options in the stated choice scenarios were described by five attributes: free flow and congested time, driving cost, toll cost (for the tolled alternatives) and, in the case of scenarios involving a time period choice, also the journey departure time. The levels for the time attributes were tailored to each respondent's reported most recent in-scope journey[4] characteristics (such as trip origin, destination, departure time, journey congestion etc.) to increase the realism of the choice options in the experiment. Congested time was defined as the journey time experienced as a result of other cars on the road. Free flow time was defined as the journey time that was possible without other cars being on the road. Approximate driving costs were calculated for the journey based on the journey distance (estimated from information on the journey origin and destination). These costs were presented to respondents in the background questions allowing respondents the chance to amend these prior to the experiment if they thought the costs did not accurately reflect their real world experience of costs.

Also, for realism and to present conditions that would encourage trade-offs, it was assumed that (over time) congestion would increase on the untolled options, that the congestion in the peak would always be higher than in the off-peak options and that the tolled option would be faster than the untolled option. These assumptions mean that it was not possible to simply apply multipliers to the main journey attributes only, but it was necessary to sometimes look at total journey times and journey time differences between alternatives. Note that such

[4] An in-scope trip was any trip that crossed one of the four harbour crossings between Sjælland and Amager as a driver or passenger in a car or van on a weekday within the last month

assumptions are not required in the application of the model findings but were only applied in the design to ensure a realistic trade-off.

Efficient experimental designs (Rose and Bliemer, 2009; Rose and Bliemer, 2014) were used to specify the combinations of attributes and levels to be presented in the stated choice scenarios. Efficient designs seek to minimise the standard errors of the resulting model coefficients. Each attribute had six levels, except for the toll attribute which had seven levels (including a zero toll). A detailed description of the levels of attributes is shown in Table 1. As can be seen, the values of attributes presented in the experiments were obtained as multipliers of reference values or other presented attributes (except for the peak toll). However, any values that were calculated using multipliers were presented in absolute terms to respondents. To ensure reasonable values in the experiments for long-distance trips, we applied adjustments for a 45-minute component of the journey (the part that would be affected by the tunnel), which was then added back on to the rest of the journey time.

Further, to emphasise the implications of time period switching, departure time information was explicitly presented to respondents for each of the alternatives. The departure time and shifting was determined based on respondents' current travel time period and their preferred travel time period. For those who travelled in the off-peak but preferred a peak departure, the time shifting information was used to tailor the SC experiment, which is a continuous departure time shift. For instance, a traveller started the journey at 6:30am to avoid the morning peak (7:00 – 9:00am), although his/her stated preferred departure time was 7:10am. In this particular situation, the departure time shift is 40 minutes (i.e. the difference between the preferred departure time and actual departure time) which is used in the tailored choice experiment.

For those travelling in the peak period, departure time changes of one and two hours were tested for the off-peak alternatives. The departure time changes were randomly assigned across individuals. In the analysis, the departure time shift was included in the model. Table 2 summarises the departure time assumptions presented to respondents in the experiments, given their time of departure and departure time flexibility.

Each respondent was presented with ten choice scenarios, with the 10th choice being an identical copy of an earlier task but where the toll for the tunnel route option was set to zero in order to examine how choices would vary with a toll of zero, for example to explore the incidence of tunnel phobia but also zero cost bias.

Table 1: Summary of attributes and levels in the stated choice survey

Route	**Time period**	**Attribute**	**Reference value**	**Levels**					
				1	**2**	**3**	**4**	**5**	**6**
Untolled route	**Peak**	Total journey time*	Reported time	2	1.7	1.4	1.2	1.1	1
		Uncongested time	Free flow time (derived from network level of services)	1	0.9	0.8	0.7	0.6	0.5
		Congested time	Total journey time minus uncongested time						
		Travel cost	Calculated/validated cost	2	1.8	1.6	1.4	1.2	1
	Off-peak	Total journey time**	Difference between total time in peak (current route) and free flow****	0.6	0.5	0.4	0.3	0.15	0.05
		Uncongested time	Free flow time	1	0.9	0.8	0.7	0.6	0.5
		Congested time	Total journey time minus uncongested time						
		Travel cost	Peak alternative cost	1	0.95	0.9	0.85	0.8	0.75
Tolled tunnel route	**Peak**	Total journey time	Observed route peak alternative total time	0.95	0.9	0.8	0.7	0.6	0.5
		Congested time	Difference between peak time (tolled route) and free flow time (LOS)	0.9	0.7	0.5	0.3	0.2	0.1
		Travel cost	Peak alternative cost (current route)	1.5	1.25	1	0.85	0.7	0.5
		Toll ***	Absolute values (DKK)	5	10	20	30	40	50
	Off-peak	Total journey time	Off peak time (observed route)	0.95	0.9	0.8	0.7	0.6	0.5
		Congested time	Peak congestion (tolled route)	1	0.9	0.8	0.7	0.6	0.5
		Total cost	Peak cost (tolled option)	1	0.95	0.9	0.85	0.8	0.75
		Toll (multiplier on peak toll)	Peak toll	1	0.9	0.8	0.7	0.6	0.5

* All levels are applied as multipliers to base levels collected as background questions, except for the toll cost which is introduced as an absolute value.
** The choice consists of two journey time elements: time in free flow traffic (uncongested time) and time in congestion traffic (congested time). The total journey time attribute is included to calculate the time elements.
*** The toll attribute has seven levels, including a value of zero (not shown), which is used in the additional (tenth) task at the end.

**** The untolled route off-peak total journey time is calculated based on the peak total time (untolled route) in the choice and the free flow time (derived from network level of service) (total off-peak time = free flow time + multiplier * [Untolled route peak total time – free flow time]).

Table 2: Summary of departure time attribute levels in the stated choice survey

Current departure time period	**Preferred departure time period**	**Untolled route**		**Tolled tunnel route**	
		Peak	**Off-peak**	**Peak**	**Off-peak**
Peak	Peak	Current departure time	Leave one or two hours earlier or later	Current departure time	Leave one or two hours earlier or later
Off-peak	Peak	Shift to preferred departure time	Current departure time	Shift to preferred departure time	Current departure time
Off-peak	Off-peak		Current departure time		Current departure time

An example of a choice scenario is presented in Figure 1 below – as can be seen, the journey time was split into free flow and congested time, where the congested time was obtained as the difference between the total and uncongested times produced by the design. In the example, for the off-peak routes, the departure time changes of one or two hours early or later were tested.

Figure 1 Example of a SC scenario

Which option would you choose for the journey you made between [your origin] and [your destination] for [your trip purpose]?

	(Option A)*	**(Option B)**	**(Option C)**	**(Option D)**
	Current route, leaving at [your preferred departure time]	**Current route, leaving at [departure time shifting]**	**New tunnel, leaving at [your preferred departure time]**	**New tunnel, leaving at [departure time shifting]**
Journey time				
- Time in freely flowing traffic	14 mins	24 mins	45mins	15 mins
- Time in congested traffic	67 mins	9 mins	4 mins	1 mins
Journey cost				
- Driving costs	18 kr.	14 kr.	9 kr.	8 kr.
- Toll			50 kr.	10 kr.

* For the sake of simplicity, we named them Options A, B, C and D in the example, subsequent equations and in the analysis. A is thus always the option of 'current route, departure at the preferred time', B is 'current route with departure time shifting', C is 'new tunnel, departure at the preferred time' and D is 'new tunnel with departure time shifting'.

In order to reduce potential order effects in the responses, the order of the alternatives (in terms of whether the tolled vs untolled, and current vs shifted departure time) and the order of the time and cost attributes were randomised across respondents.

2.3 Data collection

The data collection was conducted through a web-based questionnaire hosted and managed by KANTAR Gallup. Respondents for the survey were selected from the GallupForum panel through a screening procedure. The GallupForum panel has more than 45,000 members, who have been selected based on telephone recruitment. It is a randomly recruited panel from which stratified representative samples can be selected. Because of concerns regarding the quality of surveys derived from panels in other countries (Significance et al., 2007), the panel survey was supplemented by surveys collected from respondents who were observed to make a journey across the existing bridges. These respondents were recruited via postcard surveys handed to respondents whilst they made their journey; respondents were also recruited by phone and Facebook. Differences in results between the different ways of recruiting people was an issue that was explicitly explored in the analysis – discussed below.

For the online surveys, quotas were set to ensure that a minimum number of surveys were obtained for commute, business and other (private/leisure) journey purposes. For respondents who made multiple in-scope trips, business trips were prioritised in order to fulfil the quotas. Quotas were also set to ensure that survey responses were collected from both drivers and passengers. In addition, 19,300 postcards were handed out to car drivers and passengers while stopped at red traffic lights, spread over several sites on both sides of Langebro, Knippelsbro and Sjællandsbroen bridges. The fourth connection is a motorway, which could not be included in the postcard survey. The postcards handed out accounted for 21 per cent of the total traffic during the survey periods. The response rate for the postcard survey was 15 per cent, with 5 per cent (912 respondents) going on to complete the SC questionnaire. The survey covered the period between 7am and 7pm on several workdays.

A detailed overview of the sample in terms of key characteristics is given in Lu et al. (2018). It is emphasised that the focus of the study was to understand potential tunnel route users' willingness to pay (WTP) for a hypothetical tunnel and thus the sample reflects people who were in scope to use the tunnel and not travellers in general in Copenhagen. It is noteworthy that 87.5 per cent of the sample were car drivers. Of these, 45 per cent were making journeys for commute purposes (education trips were included with work commuting trips in the analysis). Including passengers, 42 per cent of journeys were for commuting and 20 per cent for business. The analysis in the paper makes use of the data for commuting and other non-business purposes. An overview of the data used for analysis is presented in Table 3. We observe slightly higher rates of choosing the Ring Road option for peak travellers than off-peak travellers overall, while it is higher for commuters than for others. A high rate of shifting departure times is also noted for those with flexibility, both for the tunnel and non-tunnel route options.

Table 3: Overview of sampling and stated choice behaviour

	Commuting		**Other**	
	With flexibility	Without flexibility	With flexibility	Without flexibility
Travellers in peak period				
Total interviews	1020	46	544	54
Panel (%)	49.2%	50.0%	81.4%	85.2%
Intercept (%)	50.8%	50.0%	18.6%	14.8%
Choice observations				
Current route & time (Opt A)	23.7%	44.0%	26.6%	52.3%
Current route, shifted time (Opt B)	28.3%	n/a	30.5%	n/a
Tunnel route, current time (Opt C)	19.1%	56.0%	17.1%	47.7%
Tunnel route, shifted time (Opt D)	28.9%	n/a	25.9%	n/a
Travellers in off-peak period				
Total interviews	233	345	80	713
Panel	64.0%	79.4%	78.8%	86.5%
Intercept	36.0%	20.6%	21.2%	13.5%
Choice observations				
Current route & time (Opt A)	18.6%	54.6%	14.4%	61.9%
Current route, shifted time (Opt B)	33.8%	n/a	37.5%	n/a
Tunnel route, current time (Opt C)	14.2%	45.4%	12.4%	38.1%
Tunnel route, shifted time (Opt D)	33.4%	n/a	35.7%	n/a

The survey also included a number of attitudinal questions to investigate people's attitudes about travelling in a tunnel to investigate prevalence of 'tunnel phobia'. A relatively small number of respondents in the sample stated they do not like travelling in a car in tunnels. There were only 17 respondents who stated they would never travel in a car in a tunnel.

Prior to the main survey a pilot survey was undertaken in April 2017 to check the survey questions and experiments, the recruitment procedure and survey response rates. The respondents for the pilot survey were approached via a smaller postcard survey, covering only Langebro and Knippelsbro bridges for one day. After analysis and review of the results of the pilot study, only a few changes were made to the survey questionnaire and therefore the pilot survey data were incorporated in the model analysis.

3. MODELLING ANALYSIS

3.1 Model development process

After initial data processing and cleaning, we used a systematic approach for developing the final model specification, testing the benefits of various departures from a simple base model that incorporated only generic effects for all attributes. We first looked at the inclusion of deterministic heterogeneity in preferences, linked to characteristics of the respondent. We also tested the role of data collection and design effects, looking both at impacts on error scale and preferences by the source of data collection, the type of experiment presented (two alternative or four alternative) and the order of presentation of attributes and alternatives. A key part of the analysis was focussed on the specification of the random component of utility, both in terms of the assumptions about the model error structure and the treatment of random taste heterogeneity. In our work, we were guided by recent developments in the literature and especially the work in Hess et al. (2017). For a number of components of the model specification, we went beyond that work, which is the current state-of-the-art in VTT research, notably in terms of the treatment of random heterogeneity.

In what follows, we focus on the final specification of the model for commute and other purposes. All the intermediate model test results and the results for business travel can be found in Lu et al. (2018). One point needs addressing before we proceed. Over the last two decades, a key interest in VTT work has been how stated choices are influenced by the sign of changes (i.e. losses are valued more than gains) and the size of the change (i.e. the size of the time or cost change impacts the value of the change) relative to base/reference values (see Daly, Tsang and Rohr (2014), for example). These empirical findings are related to Prospect Theory (Kahneman and Tversky 1979). In line with the recent UK VTT study, we tested reference-dependence effects for both time and cost following the state-of-the-art de Borger and Fosgerau (2008) (dBF) approach. While we identified significant reference dependence effects in the base MNL model, no significant reference dependence terms were identified in the models incorporating random heterogeneity. This is contrast with the findings in other recent studies, and may be driven in part because this study explored smaller time and cost changes in the experiment, which were limited in order to ensure realistic changes due to a new tunnel (therefore, there is less variation in the cost and time changes across people relative to their reference trips). Moreover, the changes were not especially larger for those who made longer trips, for reasons discussed earlier in the paper. With ongoing discussions about whether such reference dependence effects are in non-trivial part a design artefact (cf. Hess et al., 2020) and also the resulting difficulties in determining a reference free VTT (cf. Hess et al., 2017), this finding was not unwelcome in an applied real world study.

3.2 Model error structure

One of the first key decisions taken was whether models that incorporated an additive or multiplicative error structure best reflected the stated choices. In a random utility model, the utility is decomposed into a deterministic and a random component, the error term (e.g. Ben-Akiva and Lerman 1985). Additive models have been used in most VTT studies previously conducted, writing the utility function for alternative *i* in choice task *t* for person *n* as:

$$\mathrm{U}_{int} = \mathrm{V}_{int} + \varepsilon_{int} \tag{1}$$

where V_{int} and ε_{int} represent the deterministic and random components of utility, respectively.

The more recent Danish National VTT study (Fosgerau et al. 2007) and UK VTT study (Hess et al. 2017) instead made use of a multiplicative error structure, where the error is proportional to utility. Theoretically, this formulation can be advantageous because the utility variance increases as utility increases – in essence accommodating greater noise for longer trips. This is reasonable, as it would be our expectation that for longer trips there are more factors and larger variations that could influence decisions of which the analyst is not aware.

In the multiplicative model (MM) formulation, instead of adding to the deterministic utility, the error component is included by multiplying the deterministic part, where we use ν as the multiplicative error terms, i.e.:

$$\mathrm{U}_{int} = \mathrm{V}_{int} \cdot \nu_{int} \tag{2}$$

In practice, the multiplicative model is estimated by taking the logarithm of each side of the equation:

$$\log\left(\mathrm{U}_{int}\right) = \log\left(\mathrm{V}_{int}\right) + \log(\nu_{int}) = \log(\mathrm{V}_{int}) + \varepsilon_{int} \tag{3}$$

To implement the formulation, we need to ensure that both V_{int} and ν_{int} are positive. The error term in (2) is assumed to follow a log-extreme-value distribution, following Fosgerau and Bierlaire (2009), so that a simple logit model can be used to estimate the multiplicative reformulation in (3) as ε_{int} now follows an extreme value distribution. The multiplicative models were estimated in willingness-to-pay (WTP) space, where the logarithm of the deterministic utility V_{int} for alternative *i* is written as:

$$\log(V_{int}) = \delta_{\mathrm{i}} - \mu \cdot \log\left(cost_{int} + \sum_{k_T} \omega_{k_T} x_{k_T,int} - \sum_{k_{NT}} \omega_{k_{NT}} x_{k_{NT},int} + \kappa_{toll} Tollcost_{int}\right) \tag{4}$$

where μ is a positive scale parameter, and $\omega_{\mathrm{k_T}}$ and $\omega_{\mathrm{k_{NT}}}$ are monetary values (i.e. willingness to pay/accept) for reductions/increases or shifts in the k^{th} type of time ($x_{k_T,int}$), i.e. free flow time, congested time and departure time in the current study, and non-time utility components ($x_{k_{NT},int}$). The negative sign on the entire utility means that the $\omega_{\mathrm{k_T}}$ are positive for undesirable attributes, i.e. they relate to a willingness-to-pay for reducing the amount of an attribute; $\omega_{\mathrm{k_{NT}}}$ are negative for desirable changes. A toll multiplier is included to reflect that the impact of toll on respondents' preferences may be different from the impact of travel cost (otherwise κ_{toll} would be equal to 1). The first term in Equation (4), i.e. δ_{i}, is an alternative specific constant (ASC) for alternative *i*, where this was not included in the log-WTP part, so as to ensure that the impact of the ASC in terms of explaining underlying differences across alternatives is independent of the other attributes.

After substantial testing, we found that the multiplicative error structure also had advantages in the context of the present study, with consistent improvements in model fit. This is again not surprising given the mix of both short and long journeys, where the potential for influences on behaviour by factors unknown to the analyst clearly increases for longer journeys.

3.3 Deterministic heterogeneity

As part of the model development, we undertook a series of tests to quantify the impact of respondents' socio-economic and journey characteristics on the resulting VTTs. We also examined the impacts of the SC design and data collection approaches on the VTT estimates and the model scale. The design effects include the positioning of the time relative to the cost attribute and the positioning of the alternatives presented in the choices.

The majority of these effects were accommodated through the estimation of additional multipliers on the WTP measures. With $\boldsymbol{\omega_{k_T}}$ for example denoting the VTT for time component *k*, we would now replace this component in equation (4) by

$$\omega_{k_T,int} = \omega_{k_T} \prod_l \zeta_{k_T,l,n} \prod_m \zeta_{k_T,m,int} \quad (5)$$

where ω_{k_T} is a base valuation, and where $\zeta_{k_T,l,n}$ and $\zeta_{k_T,m,int}$ are a set of individual and alternative-individual-task specific multipliers, which we now look at in turn. This approach using specific multipliers was also used when testing for heterogeneity in the scale parameter in Equation (4), i.e. μ.

3.3.1 Person and trip characteristics

The person and trip characteristics were treated in different ways depending on the nature of the variable, making a distinction between continuous and categorical variables.

Consistent with the UK VTT study, the impacts of continuous effects – i.e. for reported income, trip distance (from the level of service data), reported journey time and reported journey cost – are represented through elasticity terms (λ), with a separate treatment for missing values. For example, among similar formulae for time, cost, distance and income, the formula for the impact of income would be one of the individual-specific multipliers (constant across alternatives and tasks) in Equation (5), given by:

$$\zeta_{income,n} = \left(\frac{\mathrm{inc_n}}{\overline{inc}}\right)^{\lambda_{\mathrm{inc}}} \delta_{\mathrm{income\ reported,n}} + \zeta_{\mathrm{income\ not\ stated}}\left(1 - \delta_{\mathrm{income\ reported,n}}\right) \quad (6)$$

where inc_n is a continuous variable reflecting the annual income reported by the respondent. In early tests we examined the impact of household income and personal income on VTT, finding that the models with personal income achieved a better model fit. This is consistent with the OTM model.

The term $\overline{inc}$ is included for normalisation and is given a value of 550,000 – this means that the base VTT estimates are for an individual at the reference income level of DKK 550,000. The dummy variable $\delta_{\mathrm{income\ reported,n}}$ is equal to 1 for respondents who report income, and zero for everyone else. We then have two estimated parameters, with λ_{inc} being an estimated income elasticity, and $\zeta_{\mathrm{income\ not\ stated}}$ being a multiplier for respondents who did not provide income. This multiplier will have a value below/above 1 if income non-reporters have a VTT for time component *k* that is smaller/larger than the VTT for an individual at the reference income. It should be noted that the income effect is generic across all valuations.

In Equation (6), $\zeta_{income,n}$ is the income multiplier for respondent n, and is used to multiply the VTT for time component k in Equation (5), which is then used in Equation (4). A similar approach was used for other continuous variables, where we estimated elasticities in relation to base cost, total travel time and distance values – for these variables, the additional multiplier for non-reporters (i.e. $\zeta_{\mathrm{income\ not\ stated}}$ in Equation 6) was not required as there were no missing values. The choice of normalisation is arbitrary, and we adopted the following as approximate average values to use in the calculation:

- Average travel distance derived from LOS data = 35 km
- Average reported journey cost = 50 DK
- Average reported journey time = 45 minutes.

These average values were obtained from analysis of the overall sample. Values are rounded for simplicity.

The treatment for categorical variables is similar, but simpler. For most of these factors, multipliers ζ on base VTTs are again used, with one category specified as the base. Using gender as an example, this specification can be written for respondent $\boldsymbol{n}$ as:

$$\zeta_{k_T,gender,n} = \zeta_{k_T,female} * female_n + male_n \quad (7)$$

where $female_n$ and $male_n$ are 1 for female and male respondents, respectively, while the parameter $\zeta_{k_T,female}$ is estimated. The inclusion of $\zeta_{k_T,gender,n}$ then ensures that the base VTT relates to male respondents, with any difference for female respondents captured by $\zeta_{k_T,female}$. Separate multipliers were applied to each of the time components: free flow time, congested time and departure time shifts, hence the subscript k_T in Equation (7). The model outputs were then examined to see if any of the impacts across different time components were significantly different from each other, and if not they were then combined across the time components. These tests were conducted for each journey purpose.

In addition to gender, we tested valuation differences across different segments by age group, income (as elasticities), car ownership, family status, tenure, education and employment. For journey characteristics, we tested valuation differences across different segments, separating by: drivers and passengers, cars and vans, journey frequency, frequency of using bridges in Copenhagen, whether the departure time is the preferred one, whether there is flexibility on the arrival time, number of passengers (adults, and children), whether the cost is reimbursed for the journey, travel time period and travel time components.

3.3.2 SC experiment design and data collection effects

As in the UK VTT study (Hess et al. 2017), multiplicative effects coding was used to take account of potential biases resulting from the position of time and cost components in the stated choice scenarios. Using the effect of time attribute position relative to the cost attribute (on top of the choice), the multiplier for use in Equation (4) is written as:

$$\zeta_{time-position,n} = \zeta_{top\ time}\delta_{top_{time,n}} + \left(\frac{1}{\zeta_{top\ time}}\right)(1 - \delta_{top_{time,n}}) \quad (8)$$

A couple of observations are needed. Firstly, this multiplier is individual as opposed to choice task specific as the order of attributes is kept constant across tasks for the same individual, where $\boldsymbol{\delta_{top_{time,n}}}$ is 1 if time is presented above cost for respondent *n*, and 0 otherwise. Secondly, the description of Equation (8) as multiplicative effects coding comes from the fact that the multiplier for the second ordering of attributes is the inverse of the first ($\frac{\mathbf{1}}{\boldsymbol{\zeta_{top\ time}}}$ *vs* $\zeta_{top\ time}$), meaning that the resulting VTT multiplier $\zeta_{time-position,n}$ will reflect the average situation (geometric mean) of the position of cost and time.

In addition, the order of the alternatives (as opposed to attributes) presented in the SP scenarios can also affect the choices. Equation (4) includes ASCs, and these could be affected by the position of the alternative. We thus estimate additional position terms, i.e. rewriting:

$$\delta_{\text{in}} = \delta_i + \sum_{p=2}^{4} \Delta_{pos,p} \cdot \left(pos_{i,n,p}\right) \quad (9)$$

where δ_i is the base ASC for alternative *i* (using the order from Table 1, i.e. current route peak and off-peak before tunnel peak and off-peak), while $\Delta_{pos,p}$ presents a shift in the ASC if the alternative is presented in position *p*, with the effect normalised to zero for position 1, and with $pos_{i,n,p}$being equal to 1 if and only if alternative *i* is presented in position *p* for individual *n*.

Lastly, for the survey data collection, we tested valuation differences across different segments by: data collection stage (pilot or main wave), data collection approach (panel or postcard recruitment) and survey device used (mobile/personal computer/tablets/others).We tested the impact of these on the valuations (through individual specific multipliers) as well as through impacts on the model scale parameters in order to understand any differences in error variances. Our extensive testing revealed no differences in either the valuations or the error variance as a function of the data collection stage, approach and device, and these effects were thus not retained in the final models.

3.4 Random components

3.4.1 Random heterogeneity

A key focus of the work was to incorporate random heterogeneity in the model of behaviour. We tested for the presence of such heterogeneity in the free flow VTT, the congested VTT and the model scale. For all three of these components, a (positive) bounded distribution is appropriate. A typical solution is to use log-normal distributions, which use an exponential of a Normal, thus bounding the resulting distribution at zero. Initial attempts with log-normal distributions led to convergence problems and problems with extreme tails to one side, which is a result of the log of the distribution being Normal, and thus unbounded itself. We instead resorted to exponentials of distributions that are themselves bounded, ensuring that the resulting transformed distribution is bounded on both sides.

For the scale parameter, we used a negative log-uniform distribution, as discussed by Hess et al. (2017), where we have:

$$\mu_n = e^{a_\mu + b_\mu U_{\mu,n}} \tag{10}$$

where a_μ is the lower bound of the distribution of $\log(\mu_n)$, b_f is the spread of the distribution of $\log(\mu_n)$, and $U_{\mu,n}$ is a standard uniform variable, distributed across individuals. In practice, in estimation, we did not set constraints on the sign of the spread parameter, i.e. b_μ could be positive or negative, meaning that a_μ is the lower/upper bound of $\log(\mu_n)$ depending on whether b_μ is positive/negative. The resulting mean ($E(\mu_n)$) and median ($M(\mu_n)$) of the distribution of ω_f across individuals are then given by:

$$\mathrm{E}(\mu_n) = \frac{e^{a_\mu + b_\mu} - e^{a_\mu}}{b_\mu}; M(\mu_n) = e^{a_\mu + \frac{b_\mu}{2}} \tag{11}$$

For the valuations of free flow and congested time, we sought to incorporate correlation[5] by introducing a term that takes a role akin to Cholesky terms with multi-variate Normals. Specifically, we used:

$$\omega_{f,n} = e^{a_f + b_f U_{f,n}} \tag{12}$$
$$\omega_{c,n} = e^{a_c + b_c U_{c,n} + s_{f,c} U_{f,n}} \tag{13}$$

where the term $s_{f,c}$ allows for correlation between the values of free flow time and congested time. The sign of the correlation between $\omega_{f,n}$ and $\omega_{c,n}$ is given by the sign of the product of b_f and $s_{f,c}$, where $s_{f,c}$=0 implies an absence of correlation. The magnitude of the correlation depends on the relative magnitude of b_c and $s_{f,c}$, i.e. how much of the random variation in the sensitivity to congested time is driven by the same random variate. The specific implementation used here implies that while the distribution of $\omega_{f,n}$ is still log-uniform, this no longer applies to $\omega_{c,n}$ if $s_{f,c} \neq 0$. This means that the formulae from Equation (11) can no longer be used and simulation is required to compute the moments. While the decision of which of the two components (i.e. $\omega_{f,n}$ or $\omega_{c,n}$) to use as the log-uniformly distributed value thus has a potential impact on the model, in practice, we found that the resulting shape of the distribution of $\omega_{c,n}$ is not dissimilar from that of a log-uniform distribution[6].

To further test the impact of the distributional assumptions, we investigated the use of the Fosgerau and Mabit (2013) approach by introducing polynomial terms in the model. While this made a difference in the model without socio-demographics, it was no longer the case in the final models. This suggests that the inclusion of the rich set of covariates helped reduce the remaining random heterogeneity to a sufficient degree to alleviate problems with the tail.

3.4.2 Correlation between alternatives

In addition to random heterogeneity, we included error components to capture correlation along the time-period as well as route choice dimensions. We use normally distributed error components (using the approach described in Walker et.al, 2007; also see Paag et al., 2001) to approximate a cross-nested structure for the four alternatives

[5] We observed that the valuations are lower in the model with no correlation than in the model where correlation between the time variables is modelled.

[6] The alternative approach is to use bivariate normally distributed draws, and then apply univariate inverse normal transforms prior to taking the exponential. This approach could substantially complicate the estimation process.

in the model, capturing correlation between the two current departure options and the two toll options. This leads to the following change from Equation (4) for alternatives A-D:

$$\begin{aligned}
\log(\mathrm{U}_{Ant}) &= \log(\mathrm{V}_{Ant}) + \sigma_{AC}\xi_{AC} && + \varepsilon_{Ant} \\
\log(\mathrm{U}_{Bnt}) &= \log(\mathrm{V}_{Bnt}) && + \varepsilon_{Bnt} \\
\log(\mathrm{U}_{Cnt}) &= \log(\mathrm{V}_{Cnt}) + \sigma_{AC}\xi_{AC} + \sigma_{CD}\xi_{CD} && + \varepsilon_{Cnt} \\
\log(\mathrm{U}_{Dnt}) &= \log(\mathrm{V}_{Dnt}) \qquad\qquad + \sigma_{CD}\xi_{CD} && + \varepsilon_{Dnt}
\end{aligned} \tag{14}$$

where σ_{AC} and σ_{CD} are the standard deviations of the error components that capture the covariance between alternatives A and C (non-toll and toll alternatives at current departure time) and alternatives C and D respectively (peak and off-peak toll alternatives). The implied correlation between the alternatives with the current departure time is then $\frac{\sigma_{AC}^2}{\sqrt{(\sigma_{AC}^2+\frac{\pi^2}{6})}\sqrt{(\sigma_{AC}^2+\sigma_{CD}^2+\frac{\pi^2}{6})}}$, while that between the two toll alternatives is $\frac{\sigma_{CD}^2}{\sqrt{(\sigma_{AC}^2+\sigma_{CD}^2+\frac{\pi^2}{6})}\sqrt{(\sigma_{CD}^2+\frac{\pi^2}{6})}}$. Separate correlation terms were estimated depending on whether respondents currently travelled in the peak or off-peak (cf. Train, 2009, Section 9.2.5).

3.5 Model estimation

Model estimation was carried out using Apollo (Hess & Palma, 2019), using 500 Modified Latin Hypercube (MLHS) draws (Hess et al., 2006) per random component per individual to approximate the multivariate integral representing the likelihood in the Mixed Logit structure. It is noteworthy that the introduction of the random variables led to a very significant improvement in the model fit (our initial model tests showed an improvement of over 8,000 likelihood units for four additional degrees of freedom). Throughout the model development, correlation between choice observations for a single respondent is taken into account (by treating the block of choices for one person as an observation, rather than working with individual choices), thus giving a more correct calculation of the standard errors.

4. PREFERRED MODEL RESULTS – COMMUTING AND OTHER PURPOSES

We initially estimated separate models for commute and other travel. However, we found that the resulting VTT for other travel was (slightly) higher than that for commute, when calculated across the survey sample.[7] This pattern is inconsistent with the evidence from most other studies, particularly the UK value of time study (2018), though it is consistent with previous Danish work (Fosgerau et al. 2007). Given the small differences, we estimated a model combining commute and other travel[8], including a purpose-specific VTT multiplier and purpose-specific income elasticity for other travel to allow us to test whether the resulting VTT values were in fact significantly different. The resulting multipliers were not significantly different from 1 – indicating that the differences in values were not significant – and therefore the adjustment terms were constrained to 1.

The parameters for the final joint commute and other model are shown in Table 4.[9] All t-statistics for multipliers are measured relative to a value of 1, i.e. testing the null hypothesis that there is no difference between the subsets for which the multipliers are introduced. The model parameters are grouped together for each component, i.e., elasticities, SP design effects and covariates. The model also contains terms to capture random heterogeneity and correlation as follows:

- distributed free flow value of time (terms a_f and b_f in Table 4)
- distributed congested value of time (terms a_c and b_c in Table 4)
- distributed model scale term: (terms a_u and b_u in Table 4).
- correlation between free flow and congested time (the term $s_{f,c}$ in Table 4)
- correlation between the two current departure time options (current route and tolled) and the two tolled options (current time and retimed alternatives) (the Cholesky terms in Table 4).

[7] The sample enumeration was undertaken on the Transportvaneundersøgelsen (TU) data, a national travel survey, from which we selected the relevant records for the corridor. The VTT values based on the sample-enumerated SC data were higher for commute than other. However, it is important to note that TU data are much more representative of person-trips than are the SC data. In this context, key variables are income and trip length.

[8] Pooling commute and other purposes led to a significant loss of model fit when compared with the combined likelihood of separate commute and other models. Compared to the combined log-likelihood (a value of -18,855) of the separate models, we lose 101 units of fit in the joint commute/other model for 46 degrees of freedom

[9] The model results for business travel can be found in Lu et al. (2018).

To understand the impact of tunnel phobia and strategic bias on the model results, we included the observations corresponding to the 10th choice (with zero tunnel costs) and re-estimated the final models. We also estimated another set of models, specifying an additional constant for the 10th choice on the toll alternative. Across both purposes we observe that the addition of the 10th choice observations has limited impact on the VTT valuation. For commute/other, we observe a slight increase in VTT (3% to 4%) and for business a decrease in the VTT value of about the same magnitude. The changes to the key elasticity parameters are all insignificant. Overall, these results lead us to believe that our findings are not substantially impacted by tunnel phobia effects nor excessively strong resistance to the idea of paying a toll (i.e. a zero-cost effect). Therefore, observations corresponding to the 10th choice are excluded in the preferred models shown in Table 4.

Table 4: Commute/other model coefficients

Observations	**27,315**		
Log-likelihood	**-18,828**		
Number of parameters estimated	**36**		
Adjusted rho-square (c)	**0.41**		
MLHS draws	**500**		
Description	**est.**	**rob se**	**rob t**
Alternative specific constants (ASC)			
ASC A - 4 Alts experiments (base = A 4 Alt) - departure in peak	0.0000	NA	NA
ASC B - 4 Alts experiments (base = A 4 Alt) - departure in peak	1.2418	0.303	4.1
ASC C - 4 Alts experiments (base = A 4 Alt) - departure in peak	0.4254	0.139	3.1
ASC D - 4 Alts experiments (base = A 4 Alt) - departure in peak	1.4439	0.336	4.3
ASC A - 4 Alts experiments (base = A 4 Alt) - departure in off-peak	0.0000	NA	NA
ASC B - 4 Alts experiments (base = A 4 Alt) – departure in off-peak	2.2371	0.478	4.7
ASC C - 4 Alts experiments (base = A 4 Alt) - departure in off-peak	0.5973	0.283	2.1
ASC D - 4 Alts experiments (base = A 4 Alt) – departure in off-peak	2.4340	0.466	5.2
ASC A - 2 Alts experiments (base = A 2 Alt) - departure in peak	0.0000	NA	NA
ASC C - 2 Alts experiments (base = A 2 Alt) – departure in peak	0.4254	0.265	3.1
ASC A - 2 Alts experiments (base = A 2 Alt) - departure in off-peak	0.0000	NA	NA
ASC C - 2 Alts experiments (base = A 2 Alt) - departure in off-peak	-0.2590	0.139	-1.9
Cholesky term, between A and C - current departure is peak period	4.4478	0.219	20.3
Cholesky term, between C and D - current departure is peak period	2.3902	0.100	24.0
Cholesky term, between A and C - current departure is off peak period	3.8576	0.474	8.2
Cholesky term, between C and D - current departure is off peak period	2.1051	0.195	10.8
Parameter of underlying uniform distribution for ln (VTT) - ω			
Free-flow time (base), lower limit (a_f)	-2.0906	0.178	-17.4
Congested time (base), lower limit (a_c)	-2.3315	0.139	-24.0
Free-flow time (base), spread (b_f)	3.6419	0.267	9.9
Congested time (base), spread (b_c)	2.8465	0.111	16.7
Correlation term for Free Flow Time and Congested Time ($s_{f,c}$**)**	1.7827	0.157	5.0
Parameter			
Departure time shifting	0.5812	0.054	-7.8†
Multiplier for toll vs. fuel cost (κ_{toll})	1.1004	0.031	3.3†
Elasticities			
The income elasticity on VTTs (λ_{inc})	0.1735	0.049	3.5
Distance elasticity on VTTs ($\lambda_{distance}$)	0.0000	NA	NA
Observed cost elasticity on VTTs ($\lambda_{obs.cost}$)	0.1900	0.053	3.6
Observed total travel time elasticity on VTTs ($\lambda_{obs.time}$)	-0.0480	0.092	-0.5
Traveller characteristics covariates (multipliers on the ω**)**			
Multiplier - the impact of reimbursement on the VTTs ($\zeta_{reimburse}$)	1.7259	0.119	6.1†
Multiplier - unreported income on VTTs ($\zeta_{\text{income not stated}}$)	0.7113	0.074	-5.0†
Departure time shifting, not departure at the preferred time (base = departure at the preferred time)	0.3911	0.097	-8.9†
Time (free flow, congestion, and departure time shifting), for female (base = male) (ζ_{female})	0.8856	0.052	-2.2†
Time (free-flow congestion, and departure time shifting), aged 60 plus (base = age 60 and below) ($\zeta_{age\ 60\ plus}$)	0.9188	0.058	-1.4†
Trip characteristics covariates (multipliers on the ω**)**			
Departure time shifting, shopping (base = other purpose, non-shopping) ($\zeta_{dep,shoping}$)	0.6797	0.153	-2.1†
Departure time shifting, escort (base = other purpose, shopping) ($\zeta_{dep,escort}$)	1.5766	0.333	1.7††
Departure time shifting, for all other purposes (base = commute) ($\zeta_{dep,other}$)	0.6183	0.070	-5.5
Scale parameters			
Scale, lower limit (a_{μ})	0.9733	0.063	15.4

Scale, spread (b_μ)	2.3442	0.115	20.4
SP design effects			
If time presented at top of choice ($\zeta_{top\ time}$) (multiplicative effects coding)	0.8835	0.029	30.2
Alternative position: if the alternative is presented as the second alternative (base = P1)	-0.1297	0.069	-1.9
Alternative position: if the alternative is presented as the third alternative (base = P1)	0.2047	0.092	2.2
Alternative position: if the alternative is presented as the fourth alternative (base = P1)	-0.1924	0.104	-1.9

† t-ratio with respect to 1.

The transformed values showing the median, mean and standard-deviation for free-flow time, congested value of time and the scale term, along with the correlation implied by the random terms introduced in ASCs and correlation between free flow time and congested time is shown in Table 6. These calculations incorporate the socio-demographic interactions.

Table 5: Transformed values for distributed variables

Ranges for distributed terms	median	mean	st. dev.
free flow time (DKK/hr)	35.7	62.5	68.5
congested time (DKK/hr)	45.8	76.1	86.8
scale	8.5	10.6	6.9
Correlation coefficients			
Alternative A and C, current departure in peak hour		0.424	
Alternative C and D, current departure in peak hour		0.772	
Alternative A and C, current departure in off-peak hour		0.448	
Alternative C and D, current departure in off-peak hour		0.779	
Free flow time and congested time		0.494	

4.1 Summary of modelling findings

Below we summarise the model findings from the final mixed multinomial logit (MMNL) models, focussing on those effects that were retained in the final model.

4.1.1 Preference between routes and departure times

The SC survey presented respondents with a choice between alternatives implying a decision on time period as well as route. We thus start our discussion by looking at the alternative specific constants. Remember that alternatives A and B related to the current route, with C and D to the tunnel route, while A and C related to the current time and B and D to a shift in departure time. The actual values need to be interpreted alongside the impacts of the explanatory variables. For example, the fact that the constants for the alternatives with a shifted departure time (B and D) are positive will be counteracted by the negative impact on utility of the continuous departure time shift attribute. Similarly, while toll road alternatives have a positive ASC except for current off-peak travellers with no desire to shift departure time, the toll attribute itself will influence utility negatively.

Turning to the correlations between the alternatives, we see higher correlation between the two alternatives with departure at the current time than between the two tolled options.

4.1.2 Overall response to travel time and travel cost

Consistent with other studies, we observe substantial random variation in VTTs for both free flow and congested time, with significant estimates for the range of the underlying uniform distribution[10]. The actual resulting VTT measures are studied in detail later. As mentioned earlier, the addition of the polynomial terms was not necessary in the final models, where the ratio of mean to median value was not as high as in interim models. However, the additional term capturing the correlation between the two valuations is significant.

The valuation for departure time shifts was not found to have random heterogeneity and is positive, in line with expectations, i.e. a positive WTP for reductions in shifts in departure time.

The scale parameter in the model follows a log-uniform distribution, with significant heterogeneity across individuals.

[10] The fact that the lower bound parameter used inside the log for the congested time coefficient is more negative than that for the free flow time coefficient implies that the lower bound on the valuation for congested time is smaller than that for free flow time, but the interest is on the mean, and this is higher for the former, as shown in Table 5.

We observe that respondents react more negatively to tolls than to other driving costs, but the differences are not large (multiplier = 1.10; t = 3.3).[11] This finding is consistent with findings from other studies (e.g. Hess et al., 2017), although the multipliers found here are lower than elsewhere. A number of hypotheses can be suggested to explain why respondents value the two cost components differently, including strategic bias against tolls but also the fact that tolls are paid per journey while driving costs are paid in a lump sum at irregular intervals (when refuelling in particular). These results may reflect short-term effects.

4.1.3 Impact of covariates and design characteristics

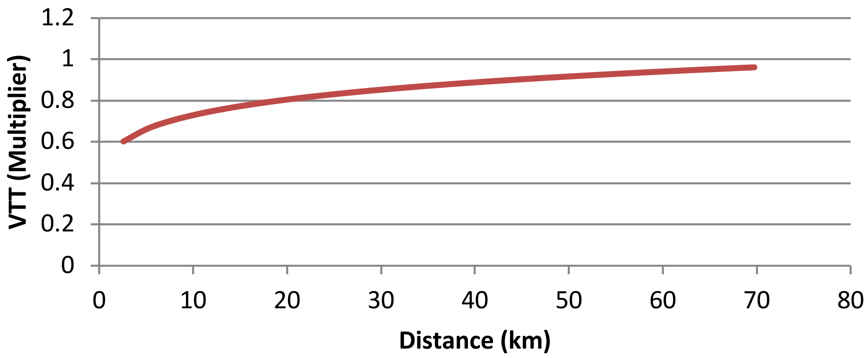
A number of significant (or nearly significant) socio-economic terms were identified in the final models. For commute and other travel, women[12] have a consistently lower VTT (even when income differences have been taken into account). People aged over 60 also have a lower VTT, although the impact is less statistically significant (t=1.40). In addition, sensitivity to departure time changes is lower for shopping and other trips, relative to those commuting, and is higher for those escorting others, e.g. escorting children to school. Respondents who were reimbursed for their commute and other travel have a higher VTT. People who did not report their personal income show a slightly lower VTT.

No significant differences for (adult) passengers were identified, compared to drivers. We also do not observe any significant differences for those travelling in vans, compared to those travelling in cars, either for commute or for other purposes.

For the continuous covariates, we find that the impact of personal income (i.e. personal income elasticity) on VTT is positive and statistically significant (0.1735, t = 3.5). This indicates higher VTTs with higher income levels, which is intuitive and consistent with the previous research (Hess et al. 2017), although the elasticity is lower than the previous evidence. While the distance elasticity is not significantly different from zero, the cost term elasticity is positive and significant (0.1900, t = 3.6), indicating higher values of time for journeys with higher costs. Lastly, the reported time elasticity is estimated to be negative (although not significant), suggesting that the value of time decreases with the total journey time. The positive cost elasticity and negative time elasticity is consistent with the recent UK study (Hess et al., 2017) and the 2013 Dutch study (Significance et al, 2013).

To ensure that the overall multiplicative effect of the distance, cost and time elasticities did not lead to counter-intuitive VTT variation, we plot the VTT multiplier arising out of the time, cost and distance effects (see Figure 2).[13] We find that the VTT multiplier increases with journey lengths, consistent with previous research. Further (regression) analysis using trips from the Danish household survey also helps to understand the impact of income, journey time, cost and distance, and socio-economic variables – which are correlated in complicated ways with income and trip length – on VTT. We find that trip length and income are roughly equal in importance, each with elasticities not far from 0.2.

Figure 2 The impact of time, cost and distance elasticity terms on VTT for Commute and Other travel



We find that if time is presented at the top in the choice scenarios, the resulting VTT is (surprisingly) lower, but the impact is not found in the business model which is not reported here.

[11] Interestingly, for business travellers we do not observe a significant difference between these terms.

[12] In early model tests, the impact of gender and age groups were included in the model separately for each of the time element (i.e. free flow time, congested time and departure time shift). However, the model results revealed that the covariates were not statistically significantly different across the three time elements and therefore they were jointly estimated (constrained) to be the same for each type of time.

[13] We expect that the overall VTT does not decrease with increase in trip length, taking account of time, cost and distance increases.

The order of alternatives presented in the SP choices can affect the alternative-specific constants, although many of the adjustments are small and many are not significantly estimated.

4.2 Application of the VTT valuations to the Ørestad Traffic Model (OTM)

The Ørestad Traffic Model system is used for forecasting demand for passenger and freight transport across the Greater Copenhagen area. The VTT valuations in OTM date back to 2004 (Tetraplan, 2005) so a key improvement in OTM model system was to update the VTT valuations from the Harbour Tunnel SC (hereafter: SC) study. To obtain VTT values for application (OTM), the discrete choice models developed from the SC data were applied to a sample of individuals and trips that represent the entire Copenhagen area. As the SC data is not a representative sample for the area, the Danish National Travel Survey (TU) was selected for use in sample enumeration. This approach is possible because the VTT model estimates are based on an exogenous sample (i.e. the sampling is not related to the SC responses) and are therefore unbiased (Ben-Akiva and Lerman, 1985), even though the sample itself may be biased.

For input to the model, VTT can be expressed as a function of income and journey length, the latter chosen because VTT is not then a function of the forecast scenario, which it would be if trip time or cost were used as the basis. It is not possible in a large-scale forecasting model to use the extensive segmentation as in the model estimated.

The sample-enumerated values represent the average VTT value [14], i.e., averaged across free flow and congested time values in the proportions observed in the SC study. The base sample used in the sample enumeration process are trips observed in the TU in the years 2006-2016, for the area defined by Greater Copenhagen. A total of 37,652 records were used. For records with missing income, it was decided that the contexts of not providing income data were different in the SC and TU data, and records with missing income in TU were therefore dropped. The price base was adjusted from 2017, the year of the SC survey, to 2015, the required base year for the forecasting models.

For comparison purposes, the previous values are also reported in the following table. For commute and other travel, the values obtained in this study ('OTM 7' in Table 6) are 12-15 per cent higher than the values that are currently being used.

Table 6 Sample enumerated VTT values for car and van travellers by purpose, 2015 DKK/hr

Purpose	VTT (average for car and van travellers, DKK/hour, 2015 prices)		
	OTM 7 (using our results)	Previous OTM	Ratio
Business	172.1	98.6	1.75
Commute	72.4	64.6	1.12
Other	63.1	55.1	1.15

We observe that for the business purpose, the new VTTs are much higher (75%) than the previous values. This can partly be explained by the fact that the previous business values were estimated using a different approach (from the route choice model). The business VTT values from this study provide the first Danish VTTs for business users in the context of a demand forecasting model (i.e. distinct from welfare calculations). All else being equal, we find that business users are more likely than other travellers to use the new toll route.

Regressions were run to predict VTT as a function of income and trip distance: variables which are available in the OTM models. The variation of VTT by distance and income allows for introducing a cost damping mechanism in the model which was not possible using the previous DATIV VTT values. The regressions used a log-log form for dependent and independent variables with VTT being the dependent variable and income and distance being the independent variables respectively. Using this formulation means that the parameters for income and distance can be directly interpreted as elasticities. For all three purposes, the fit of the regression to the data was significantly better when both income and distance variables were included in the regression than regressions with just income or just distance. The estimated elasticities for the three purposes in the Harbour Tunnel study are summarised in Table 7.

[14] Two separate estimates were made for the values of free-flow time and congested time and these differ by a constant factor only as in the model. The overall average values were calculated using the travel times reported by respondents for free flow and congested in the SC surveys. For more details of the calculation, please see Lu et al. (2018).

Table 7 VTT elasticity estimates

Purpose	Income	Distance
Commute/education	0.187	0.161
Business	0.117	0.330
Other	0.197	0.155

Using the VTT elasticity estimates, the VTT by income and distance travelled is calculated in the OTM mode-destination choice models as follows:

$$VTT_{\mathrm{I,d}} = VTT_A \times \left(\frac{I}{I_A}\right)^{\eta_I} \times \left(\frac{d}{d_A}\right)^{\eta_d} \tag{14}$$

where: $VTT_{I,d}$ is the value of time for income I and distance d
VTT_A is the average VTT
I_A is the average income
d_A is the average one-way distance
η_i and η_d are the elasticities estimated in the model for income and distance respectively

5. CONCLUSIONS AND POLICY IMPLICATIONS

As outlined in the introduction, the rapid development of modelling approaches in VTT research has often failed to make the transition to real world studies with short turnarounds or to those that aim to produce results that can be implemented directly in existing forecasting systems. The study reported in this paper sought to address this shortcoming in the context of an applied study looking at the willingness of car and light van travellers in the Copenhagen area to pay to use the proposed new toll ring route, specifically around the calculation of their values of in-vehicle travel time savings.

To answer the research question, we conducted a stated choice survey in the Copenhagen area. 3,688 respondents participated in stated choice survey, providing a sufficient database for robust model analysis. The modelling work made use of the state-of-the-art specification from the recent UK national VTT study (Hess et al., 2017), expanding on it in the context of correlation between alternatives.

As in the UK VTT study, we found that improved model performance was obtained by adopting multiplicative (as opposed to additive) error structures in the discrete choice models. Multiplicative error structures provide more flexibility for capturing heteroskedasticity, especially for data that contains a mix of trip lengths. Unlike the UK VTT study and many other studies, we found no evidence of reference dependence, otherwise known as size and sign effects. A potential reason for this is the more complex nature of the SC scenarios. This may be consistent with the argument in Hess et al. (2020) where it is argued that reference dependence in SC surveys may in part be an artefact of simple surveys.

We identify and quantify significant continuous income, cost, distance and time elasticities in the models, indicating that travellers with higher (personal) incomes have higher VTTs, as do those making longer journeys. We observe that the design of the experiments – specifically the ordering of the time and cost information – impacts the resulting values of time. The resulting VTTs reflect the average of time or cost being presented first. Importantly, and in contrast to other studies that have collected data from panel and intercept surveys, we observe that the values were not significantly impacted by the survey methodology.

We observe substantial random variation in VTTs and significant correlation between time period and route alternatives, influencing the choice cross-elasticities.

We also observe that respondents react more negatively to tolls compared to other driving costs, but the differences are not large (estimated at 10%). We do not observe significant tunnel phobia or zero-cost effects; in fact we observe a positive constant for the tunnel route option over and above the toll and travel time savings.

A key aim of the work was to transfer the findings to real world application. To obtain average values for application, the final models were applied to a sample of individuals and trips in the Copenhagen area, drawn from the TU. A prototypical sampling procedure was set up to calculate average VTT values for use in forecasting demand and appraising the new tunnel investment. For commute and other purposes, the new VTTs are 12-15% higher than the previous values, once corrected for income growth since 2004. While not reported in detail in the present paper, for the business purpose, the new VTTs are higher (75%) than the previous values, though the previous business values were estimated using a different approach. The importance of using advanced model specifications and up-to-date local preference data is clear.

The new VTTs were used in the OTM 7 model to appraise the value of the Copenhagen East Ring project, the first toll road in Denmark.[15] For the first time in the 25-year history of the OTM model, the same VTT are applied both in the demand and assignment parts of the model, ensuring consistency of the applied VTTs across the entire model. Different toll scenarios were tested – including tolls based on distance travelled on the East Ring road and time of day, i.e. morning/afternoon peak vs. the rest of the day. The OTM model findings showed that introduction of any type of toll decreases the traffic on the ring road dramatically. That has been accepted by the Danish transport authorities also because similar results were obtained in the past. It can be therefore stated that the SC approach has helped in getting robust forecasts in the project, especially when testing different tolls across the day. Second, the East Ring road is a detour for many existing car trips through the city. Therefore, having new VTTs that are distance-related helped improve the forecasts. Finally, including income directly in the new VTTs is essential in a toll project such as Copenhagen East Ring toll road. The impact of tunnel phobia (examined in the SC experiment) was not applied in the project.

The lessons that were learned from the experimental design include:

- Use of multiple ways of recruiting people for the survey was successful in terms of obtaining a sizeable sample. We did not find significant differences in VTT valuations between those recruited from the survey panel and those who were recruited during a trip. This finding is in contrast from what others have found (for example see Significance et al., 2007, who found significantly lower values of time from Dutch respondents recruited through a panel).
- Including both route and time period choice in one experiment allowed the estimation of all necessary values, which avoided challenges of getting different values in different experiments.
- The experimental design included a large number of attribute levels, allowing us to obtain significant terms describing values of time and their distributions.
- In the end the careful thinking and complex calculations underpinning the choices ensure that choices were presented to people are realistic, which we believe contributed to the success of the experiments.

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[15] See: https://www.vejdirektoratet.dk/api/drupal/sites/default/files/2020-08/%C3%98stlig%20Ringvej_Sammenfattende%20Rapport.pdf

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