Denne artikel er publiceret i det elektroniske tidsskrift
Udvalgte Artikler fra Trafikdage på Aalborg Universitet
(Selected Proceedings from the Annual Transport Conference at Aalborg University)
ISSN 1903-1092
www.trafikdage.dk/artikelarkiv
Modtaget 30.09.2014
Godkendt 29.10.2015

Building efficient stated choice design for departure time choices using the scheduling model: Theoretical considerations and practical implementations

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Abstract

Modelling departure time is an important step in forecasting traffic demand. The purpose of this research is to contribute to the data collection field when studying departure time choices. Differently from the majority of the previous studies we used an efficient stated preference (SP) experiment. The objective in an efficient design is to construct a stated preference experiment which minimizes the standard errors of the estimated parameter in the model. Thus, the benefits of using an efficient design are more robust parameter estimates and/or that it allows using smaller sample sizes. However, building experimental designs for the departure time is challenging for two main reasons: 1) interdependence among attributes, and 2) realism in the choice tasks. To ensure realism, we customized the choice task based on the trips described by each individual in a trip diary and on the departure time needed in order to be at work at their preferred arrival time. However, with efficient designs it is not possible to customize the SP for each individual, unless the real trips are known before optimizing the SP design. To overcome this challenge, six different designs were constructed based on predefined travel times (10, 20, 30, 40, 50, and 60 minutes). Respondents were presented with the design which was closest to their reported travel time in the trip diary. The design was simulated using almost 20.000 observations, and was adjusted until the design was stable and the prior parameters could be recuperated.

Keywords: data collection, stated preference, experimental design, efficient design, departure time choice.

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1 Introduction

Congestion is an increasing problem, and the time of departure (especially in rush hours) becomes more and more crucial in terms of avoiding congestion. This makes it increasingly important to study departure time choice, especially morning commute trips to work. When doing so, the scheduling model (1982) is often used. The scheduling model is based on the bottleneck theory (Vickrey, 1969), and consist of a trade-off between travel time and penalties for rescheduling, i.e. being early or late.

However, an equally important part of studying departure time choice is the data collection, as the data quality is of crucial importance in the modelling phase. The purpose of this paper is to describe the entire process of how the data was gathered from design to data collection, and discuss upsides and downsides when applied to our empirical departure time study in the Greater Copenhagen Area. We refer to Thorhauge (2015a) for more details and an overview of the full scope of the project.

Departure time have been studied using both *revealed preference* (RP) data (Coslett, 1977; Small, 1982; Hendrickson and Planke, 1984; Small, 1987; Chin, 1990; Small et al., 1995; 1998a; Bhat, 1998b; 1998c; Steed and Bhat, 2000a; 2000b; Bhat and Steed, 2002), *stated preference* (SP) data (de Jong et al., 2003; Ettema et al., 2004a; 2004b; Hess et al., 2007a; 2007b; Tseng and Verhoef, 2008; Börjesson, 2007; 2009; 2012; Arellana et al., 2012), and some studies estimated models based on joint RP-SP data (Börjesson, 2008; Tseng et al., 2011; Koster and Verhoef, 2012; Kristoffersson, 2013). Both have advantages and disadvantages. The advantages of RP data is that it captures actual behaviour, thus is less sensitive to the distortion that can occur when using SP-data. On the other hand SP-data consists of hypothetical trade-offs, which makes them particularly useful for model estimation, since they can be designed with sufficient variation to enable good model estimates. In addition to that, SP-data allows for inclusion of alternatives which are currently not available (Hensher, 1982; Louviere and Hensher, 1983) or different from the existing ones (Hensher and Louviere, 1983). Studies have shown that individuals are capable of dealing with the hypothetical nature of SP-data (Louviere et al., 2000). For an in-depth discussion of advantages and disadvantages of RP and SP data, see e.g. Adamowicz et al. (1994) and Hensher (1994).

When building SP experimental designs it is common practice to do so by defining a set of alternatives, attributes and different levels (i.e. values) of the attributes. The *full factorial design* consists of all possible combination of choice sets. However, normally the full factorial design is extremely large, hence making it impractical (or impossible) to cover all possible combinations of choice tasks. Therefore, common practice is to select a subsample of the full factorial design to be used, i.e. a *fractional factorial design*. Another benefit of sampling choice tasks is to avoid choice sets where one alternative is dominant, i.e. better across all attributes.

Traditionally *orthogonal design* was the main way to build SP experimental designs. A design is orthogonal if the attribute levels are balanced and all the attributes in the design are uncorrelated, i.e. that the parameters can be estimated independently (ChoiceMetrics, 2012a). However, in recent years, a new design method has gained popularity, i.e. *efficient designs*, which build upon the idea first presented by McKelvey and Zavoina (1975). The objective in an efficient design is to minimize the standard errors, which increases the robustness of the parameter estimates. However, Kuhfeld et al. (1994) stress the importance of not categorizing a design as being efficient or not, but treat efficiency merely as a measure of "goodness" of the design. High efficiency equals low variance in the estimated parameters. For simplicity, however, we will refer to designs which aim to minimizing the standard errors as "efficient designs".

The advantage of the orthogonal designs is that parameter estimates are independent, and that orthogonal designs are often more robust than efficient designs (Walker et al., 2015). The advantage of efficient designs is that it - given the right prerequisites - outperforms the traditional orthogonal designs, see Rose et al. (2008) and Rose & Bliemer (2008; 2009). Another - and more practical - benefit of the efficient design is that smaller sample size is needed (compared to orthogonal design all else equal) to obtain equally good parameter estimates (Rose and Bliemer, 2009; 2013). The downside of efficient designs is that they are normally more complicated to build. Another disadvantage regarding the efficient design is the need of a prior knowledge of the estimated parameters, which is not always easy to obtain – and this makes the design sensitive to a misspecification of the prior parameters, i.e. if the assumed prior parameters is not a good representation of the underlying true parameters. The importance of the prior parameters is highlighted by Rose and Bliemer (2009), that states that good information about the prior parameters are more important for minimization of the standard error than having a large sample size. Hence, having a fixed pool of money to conduct a survey, Rose and Bliemer (2009) recommends to (spend some of the money to) conduct an initial pilot study in order to obtain information about the true (and thus the prior) parameters, rather than spending all the money for the final sample (thus having prior parameter information of lesser quality and precision). For a detailed theoretical and practical walkthrough of how to construct both orthogonal and efficient designs we refer to the Ngene-manual (ChoiceMetrics, 2012a).

Another important aspect of departure time choices is whether to treat time as continuous or discrete. The advantage of the continuous approach is that it does not suffer from a loss of temporal resolution due to an (often) arbitrary division of time into periods or points (Lemp et al., 2012). The advantages of the discrete approach, however, are numerous. A discretization of time usually goes hand in hand with the random utility maximization (RUM) theory, which is linked with the underlying micro-economic framework of behaviour. Furthermore, current transport models often rely on Random Utility Maximisation (RUM) for other transport choices, which allow an easier integration. In addition, it allows for computing consumer surplus (de Jong et al., 2007; Kockelman and Lemp, 2011). Finally, it can be argued that people (when dealing with departure time) perceive time in rounded intervals. Within departure time some studies have treated time as continuously (Mannering et al., 1990; Mahmassani et al., 1991; Hamed and Mannering, 1993; Lemp and Kockelman, 2010; Lemp et al., 2010; 2012), albeit the majority of studies have converted the choice into a discrete framework (Small, 1982; 1987; Hendrickson and Planke, 1984; Small et al., 1995; 1999; 2000; Noland and Small, 1995; 1998; Small and Lam, 2001; de Jong et al., 2003; Hess et al., 2007a; 2007b; Börjesson, 2007; 2008; 2009; 2012; Arellana, 2012; Arellana et al., 2012; Lizana et al., 2013; Kristoffersson, 2013). We refer to Thorhauge (2015a) for a more thorough literature review.

For this study it was decided to collect discrete Stated Preference data using an efficient design. This was done for a number of reasons:

- First of all, it was decided to discretize time mainly for two reasons: 1) even though time is continuous, people do not consider and differentiate every single second – or minute – but tend to treat time in rounded intervals (Coslett, 1977; de Jong et al., 2003; Börjesson, 2007; Hess et al., 2007a) and 2) the behavioural framework underlying discrete choice models is well-known and firmly grounded in the micro-economic theory (something continuous models cannot claim). Thus, by discretizing time it allows us to utilize the powerful toolbox of discrete choice models available to estimate models.
- Second, SP data was chosen since they possess several advantages over RP data that was considered highly desirable for this study: 1) the strength of SP data is that a high level of variation in the choice task can be insured, thus helping to improve model estimations later on, 2) the SP design allow to capture hypothetical choice situations, which allowed to include TC (as road pricing/toll rings have been highly debated in Copenhagen recently (Nielsen and Kristensen, 2011)), and 3) SP designs allows to collect multiple choice task per respondent, thus less individuals is needed in the data collection phase. In particular, this was important since the full questionnaire was very detailed, and thus very long, making it challenging to have individuals to complete the questionnaire. Therefore it was extremely valuable to be able to collect numerous choice tasks per respondents.
- Third and lastly, a strong motivation for choosing an efficient design was 1) for the purpose of research, since – to our knowledge – Koster and Tseng (2009) and Arellana et al. (2012; 2013) are the only examples of efficient designs for departure time choice, however none have constructed a fully efficient design for departure time modelling pivoting around a reference alternative, and 2) an efficient at the same time will help in reducing the number of respondents needed, which, as mentioned previously, is a highly desired feature for this study.

Designing efficient SP surveys for departure time models is not a straightforward process for a number of reasons highlighted later on. The purpose of this paper is to describe the process of creating the efficient stated choice design from start to end. The structure of the remaining of this paper is as follows. Section 2 will describe the general process of defining levels etc., while section 3 will focus specifically on the challenges faced in building stated choice designs for departure time models. Section 4 will cover the convergence process towards the final design, while section 5 will describe the remaining of the questionnaire as this is linked with the stated choice experiment. Finally the paper will summarize with the concluding remarks.

2 Modelling of departure time choices

When constructing an efficient design it is necessary to define the model specification prior to the design phase since the design is tailored specifically to the model specification. For that, we rely on the scheduling model (SM), which was first formulated by Small (1982), and have since been the dominant way of modelling departure time choice (Small, 1982; 1987; Hendrickson and Planke, 1984; Small et al., 1995; 1999; 2000; Noland and Small, 1995; Noland et al., 1998; Small and Lam, 2001; de Jong et al., 2003; Hess et al., 2007a; 2007b; Börjesson, 2007; 2008; 2009; 2012; Arellana et al., 2012; Kristoffersson, 2013). In the scheduling model it is assumed that individuals aim for a specific preferred arrival time (PAT) at the destination when choosing departure time, hence making it useful to model commuting trips, since most people (prefer to) go to work during the rush hours (Day et al., 2010). Ultimately, the scheduling model is based on the concept of trading between travel time and penalties for rescheduling, i.e. being early or late. The scheduling model assumes that travellers are faced with a discrete number of alternative departure times and they choose according to the following utility specification:

$$V_{int} = ASC_i + \beta_{TT} \cdot TT_{int}(DT_{int}) + \beta_{TC} \cdot TC_{int}(DT_{int}) + \beta_{SDE} \cdot SDE_{int} + \beta_{SDL} \cdot SDL_{int} \quad (1)$$

Where V_{int} is the utility for individual *n* associated to alternative *i*, in choice task *t* and ASC_i is the alternative specific constant for alternative *i*. TT is the total travel time from origin to destination, which in principle is a function of the departure time (DT), hence the notation $\mathrm{TT_{int}}(\mathrm{DT_{int}})$. Similar TC is the travel cost with respect to DT, while SDE and SDL are the scheduling delays, i.e. the cost of arriving early or late, respectively, and are defined as:

$$SDE_{int} = \max(-SD_{int}; 0) \text{ and} \quad (2)$$
$$SDL_{int} = \max(0; SD_{int}) \quad (3)$$

The Schedule Delay (SD) is defined as the difference between the Preferred Arrival Time (PAT) and the actual Arrival Time (AT) of alternative *i*, and AT must be equal to the departure time plus the total travel time, i.e. the SD for alternative *i*, individual *n* and choice task *t* is defined as:

$$SD_{int} = AT_{int} - PAT_n = DT_{int} + TT_{int} - PAT_n \quad (4)$$

If a traveller arrives at his or her preferred arrival time then SDE and SDL will be equal to zero. This yields that the individual will not experience disutility from rescheduling. However, TT is not constant, and it consists of different parts, as stated in (Fosgerau et al. 2008):

$$Travel\ Time = free\ flow\ time + systematic\ delay + unexplained\ delay \quad (5)$$

An extension of the scheduling model acknowledges the fact that travel time variability (TTV) plays a role in the choice of departure time. Based on the literature travel time variability have been included in two distinct ways: 1) expected travel time, and 2) mean variance. However, some authors (Noland et al., 1998; Small et al., 2000; Börjesson, 2007) recommend using the approach of expected travel time. Hence in this study the travel time variability is included as the expected travel time, E(TT). Given a series of *S* different travel times for each alternative *i* and choice situation *t*, the expected travel time is the sum of the travel time weighted by the probability (p_s) that each travel time occurs:

$$E(TT_{int}) = \sum_{s=1}^{S} p_s \cdot TT_{ints} \quad (6)$$

And equations (2) and (3) will be written as:

$$\mathrm{E}(\mathrm{SDE}_{\mathrm{int}}) = \sum_{s=1}^{S} \mathrm{p_s} \cdot \mathrm{SDE}_{\mathrm{ints}} \quad (7)$$

$$\mathrm{E}(\mathrm{SDL}_{\mathrm{int}}) = \sum_{s=1}^{S} \mathrm{p_s} \cdot \mathrm{SDL}_{\mathrm{ints}} \quad (8)$$

Note that $\sum_{s=1}^{S} \mathrm{p_s} = 1$.

3 Design a stated choice design for the scheduling model

One of the most important aspects in generating the design (regardless of using an efficient or orthogonal design) is to ensure realistic attribute values in the choice task which are presented to the respondents, i.e. the travel time presented to the individuals in the choice task should be similar to the travel time that individual actually faces in real life. First step in achieving this for departure time studies is to customize the choice task specifically for each single individual based on his or hers travel characteristics (such as departure time and travel time), hence generating alternatives based on their actual trips. This can be achieved by using a pivot design, in which the alternatives are generated from a reference alternative (Rose et al., 2008), i.e. their current commuting trip. According to Rose and Bliemer (2009), using respondents' experience (e.g. through a reference alternative) have also been recognized in a number of theories within both behavioural and cognitive psychology, but also within economic theories, e.g. prospect theory, case-based decision theory and minimum-regret theory.

However, in order to build a customized efficient pivot designs the travel characteristics (travel time and departure time) of the individual is required before hand. Since this would require the respondents to be contacted more than once (first to collect trip information, and later – after the efficient design have been generated based on the reference trip – to contact them again to answer the customized choice task), a 2-step data collection phase was not considered to be optimal. To avoid contacting the respondents multiple times, a number of "travel characteristic"-categories where predefined, and then each respondents were assigned to the group which where closest to his or hers travel characteristics. In that way it is possible to maintain a realistic choice set while at the same time using a 1-step data collection phase.

The downside of this approach is that the number of predefined groups quickly becomes rather large, making it very time-consuming building an efficient design for each specific group. To reduce the number of predefined groups it was decided to pivot the design around the preferred arrival times instead of the actual arrival time. By pivoting around the preferred arrival time the number of categories collapses into far less predefined groups which are solely dependent on the number of groups predefined for travel time. In addition, if the actual arrival time of the respondent is equal to their preferred arrival time, then the two methods are identical.

Finally, building the design around the preferred arrival time has an additional benefit, i.e. the trip which the individual reports might already be rescheduled (compared to the preferred/intended trip), and generating alternatives from a trip which is already rescheduled may potentially lead to an unrealistic alternative, which is far from the departure time that a specific individual might consider.

Below we will – given the framework outlined above – describes the choices made in building the efficient stated choice design, and more specifically how many (and which) departure time alternatives, attributes, levels, and prior parameters to use. Finally, we will also discuss the target sample to which the design is to be presented.

3.1 Alternatives

The *alternatives* represents the choices (i.e. the *choice set*) among which the respondent will make his or hers choice. When deciding on the number of alternatives to include, it is a balance between whether to construct a simple design with few alternatives or a more complex design with a higher number of alternatives. According to the micro-economic theory the choice set should be 1) exhaustive (i.e. include all available alternative), 2) mutually exclusive, and 3) differentiable. Hence according to point 1 this yields departure time alternatives which are (very) close to resemble continuous time, however, that would ultimately defeat the purpose of utilizing discrete choice models, and likely conflict with point 3. On the other hand, leaving out alternatives may cause the choice to be skewed.

Within departure time choices many studies have used binary choice designs, i.e. designs in which the choice set consists of two alternatives (Small et al., 1995; Hollander, 2006; Börjesson, 2007; 2008; 2009; 2012; Koster et al., 2011; Tseng et al., 2011). The main benefit of binary choice experiments is the simplicity of the design, making it easier for the respondents to comprehend and evaluate the alternatives (and their attributes). However, recent literature indicates that respondents can comprehend rather complex designs (Chintakayala et al., 2009; Caussade et al., 2005), making use of (too) simple designs unnecessary (Hess and Rose, 2009). In fact, according to Hensher (2006) including all important alternatives may improve the data quality. Another study by Bliemer and Rose (2009) compared the results from different studies (of the same choice) with designs ranging between 18 and 108 alternatives. It shows that an efficient design with specific selected alternatives leads to smaller standard errors, than an orthogonal design with 108 alternatives. According to Hess and Rose (2009) this results indicates that a design with a high number of alternatives does not (necessarily) lead to a better model estimation, despite the theoretical foundation. Caussade et al., (2005) recommends to use four alternatives, as this seems to be the optimum trade-off between simplicity and having a design covering the full choice set (in most cases), albeit to our knowledge Tseng et al. (2005) is the only study within departure time using four alternatives.

In this study it was chosen to follow the approach seen in Arellana et al. (2013; 2012) and Lizana et al. (2013), thus defining three departure time alternatives in each choice set. The reason for this is twofold: firstly the literature has shown that three alternatives are definitely not too many alternatives to allow the respondents to evaluate and compare the alternatives upon making a choice. Secondly three alternatives allow for an intuitive choice set structure, where respondents will be able to choose between departing around the same time as they would normally do, while offering two rescheduling alternatives – one departing earlier and one departing later. This setup was found to be intuitive. It is important to note that when presented to the respondents the alternatives were unlabelled, thus simply denoted A, B, C. This was done to avoid the choice to be affected by prior preferences without evaluating the characteristics of each alternative.

3.2 Attributes

Designing a stated choice design for the SM is complicated since the design attributes (which are presented to the respondents) and the model variables (which enters the utility function) is not a strictly one-to-one relation as seen in most choice situation (e.g. mode choice or route choice) (Koster and Tseng, 2009).

More specifically, in departure time choices attributes are interdependent. For example the travel time (TT) and travel time variability (TTV) is dependent the on the departure time (DT). Similarly, the scheduling delay is dependent on TT, TTV and DT, as well as the preferred arrival time PAT, according to eq. (7) and (8).

Travel time variability can be presented in different ways. One way is to present day-to-day travel time variation (Koster and Tseng, 2009). Another way is to have a fixed travel time, with a travel time variability which occurs occasionally (e.g. once a week) as done seen in Tseng (2011) and Arellana et al. (2013; 2012). Finally TTV can be presented as a probability of being late as done by Koster (2011) in a study on departure times for trips to the airport.

In this study travel time variability are incorporated in the stated choice design by following the approach of Arellana et al. (2012; 2013) and Tseng et al. (2011), using a deterministic probability of facing unexpected delays. This approach was chosen since TTV is not the main focus of this study, albeit we recognize that TTV can influence the departure time choice, and hence cannot be completely excluded. We defined the probability of being late to 20%, hence equivalent to being late once a week (assuming five working days per week).

3.3 Levels

A key element in designing the stated choice experiment is to define the *attribute level range*. Ultimately, the level values will determine the trade-offs respondents are facing when presented with the choice tasks. A high attribute level range is preferable from a theoretical statistical point of view. On the other hand, however, it is important to narrow the range of the attribute level to only consist of realistic values for the respondent, since although a wide attribute level range may improve the parameter estimation, the respondent will not (easily) be able to relate to attribute values which is too far away from their current trip.

Initially 5 levels where chosen for all attributes as seen in a previous study by Arellana et al. (2012). However, the fully efficient design in this project gave cause to complexities and computational problems. The computational problem where mainly due to a high number of constrains needed in the design script. The constraints are needed to ensure that the interrelation between attribute levels match according to the conversion needed between design attributes (for which the levels are defined) and model attributes (for which the efficient design is generated), as highlighted in table 1. To overcome these problems the number of levels where reduced to three levels for DT, TT, and TTV. Since TC didn't gave rise to the need of any constrains, this attribute was unaffected, but it was chosen to reduce the number of levels for this attribute as well in order to have a more "equal" design among the attributes. Ultimately we selected to have four levels for TC. The final level values are discussed later.

Design attributes Presented to the respondent	**Model attributes** Included in the model specification
• Departure time (DT) • Travel time (TT) • Travel time variation (TTV) • Travel cost (TC)	• Expected Travel Time (ETT) • Expected Scheduling Delay Early (ESDE) • Expected Scheduling Delay Late (ESDL) • Travel cost

Table 1: Design and model attributes for the scheduling model Koster and Tseng, 2009.

3.4 Choice task

One of the benefits of SP-data is the ability to collect numerous choice tasks per respondents. In our design we needed a minimum of 25 choice tasks due to the restrictions formed by the constraints mentioned above. According to Bliemer and Rose (2009) stated choice experiments have been conducted ranging from 1 to 25 choice tasks per respondent, so it might be possible to have one respondent answering all 25 choice tasks. However, we did not think it was feasible to present each respondent with a total of 25 choice tasks, since the questionnaire is quite time consuming. Other departure time studies who have relied on SP-data have presented the respondents with a total of 8 (Börjesson, 2007; 2008; 2009; 2012), 9 (Small et al., 1995; Noland et al., 1998; Hollander, 2006), 10 (Koster et al., 2011; Tseng et al., 2011), 11 (Tseng and Verhoef, 2008), 13 (Arellana et al., 2012), 15 (Tseng et al., 2005), or 16 (de Jong et al., 2003) choice task per respondents. Ultimately, we decided to use a blocking design with a total of 27 choice task, hence three blocks consisting of 9 choice task (per respondents).

3.5 Prior parameters

As briefly mentioned in the introduction, when building efficient designs, the aim is to minimize the standard error of the parameters in the model specification. This is done by utilizing the asymptotic variance-covariance (AVC) matrix. The AVC matrix can be derived if the parameters are known. However, the purpose in the modelling phase is to estimate the parameters, hence these are not known. To overcome this problem the efficient design make use of (some level of) prior parameter information as a best guess towards the true parameters. Defining the prior parameters is crucial for the performance of the efficient design, which is very sensitive to a misspecification of the priors (see e.g. Walker et al. (2015) for a comparison of the robustness of different design types). Different strategies exist when defining the prior parameters (Rose and Bliemer, 2009). The first method assumes the parameters equal zero. The second method assumes that the prior parameters are non-zero and known with certainty, hence a single value is assumed for each parameter. The third method (known as Bayesian efficient designs) was introduced by Sándor and Wedel (2001) and relaxes the assumption in the second method, by assuming the prior parameters as a distribution (Bliemer et al., 2008). Finally, a fourth method is proposed by Kanninen (2002), in which the design is updated during the collection phase as the knowledge of the true parameters increase. It goes without saying that, the better information about the prior parameters, the better the efficient design will perform, hence assuming all prior parameters to zero was quickly ruled out. Due to the difference in the model and design attributes in departure time choices, method three and four were disregarded in order not to complicate unnecessarily. Instead we relied on previous departure time studies to help define the prior parameters.

Based on previous departure time studies it should be expected that $0 > \beta_{SDE} > \beta_{TT} > \beta_{SDL}$, or at least $0 > \beta_{SDE} > \beta_{SDL}$ (Hendrickson and Planke, 1984; de Jong et al., 2003; Hess et al., 2007a; 2007b; Börjesson, 2007; 2008; Asensio and Matas, 2008; Koster et al., 2011; Arellana et al., 2012; Koster and Verhoef, 2012). The signs of all the parameters are expected to be negative; hence an increase in e.g. travel time would decrease utility. In addition, Börjesson (2009) made a meta-analysis of the ratio of parameters of SDE and SDL with respect to the parameter for TT, as seen in table 2. These ratios where then sought to be maintained in the calibration phase of the design. Different prior parameters were tested in the calibration phase. The prior parameters used in the final design will be discussed in section 4.

Studies	**SDE/TIME**	**SDL/TIME**
Small (1982), commuters	0,61	2,40
Noland et al. (1998), commuters	0,97	1,31
Dutch, commuters, flexible hours	0,89	0,63
Dutch, commuters, fixed hours	0,72	1,17
Dutch, other trips	0,96	0,94
West Midlands, commuters, flexible hours	0,77	0,79
West Midlands, commuters, fixed hours	***1,70***	***7,15***
West Midlands, other trips	0,67	0,87
Present study, commuters, flexible hours/ other trips	0,80	0,82
Present study, commuters, fixed hours/ school trips	***1,47***	***3,38***
Present study, business trips	0,71	1,06
Average across all values	0,93	1,87
Average without outliers	***0,79***	***1,11***

Table 2: Meta-analysis of the ratios between SDE/TT and SDL/TT (Börjesson, 2009).

3.6 Target sample

Defining the target sample is often equally important to building the stated choice experiment itself, since the design is often tailored for the target sample. In our case we defined our target sample as individuals who commute to work in the morning rush hour using their car. A key concern in the design phase was how to deal with individuals who (already) have a preferred arrival time at the edge of the morning commute rush hour, hence they avoid (some of the) congestion while arriving at their PAT, i.e. no rescheduling delay. The tricky part – especially when presenting both an earlier and later departure time option – is to maintain realism among the alternatives presented to the respondents, while still offering alternatives which are not dominated by their current departure time. In order to limit the skewness in realism we decided to narrow the time interval of interest until the travel time distribution can be considered (somewhat) uniform.

However, in the end we loosened this restriction slightly in order to increase the potential sample population. Ultimately, we defined our target sample as individuals who:

- Commute to work by car
- Have a travel time between 10-60 minutes to work
- Experience congestion on the way to work (i.e. traveling towards the city centre)
- Arrive at work between 7:00-9:00 AM
- Are between 18-65 years

The choice of focusing on morning commuting trips to work towards the city centre is quite typical in the studies on departure time given the distinct peak in demand for travel (Fosgerau and Karlström, 2010) and is motivated by the fact that Copenhagen (like most modern cities) faces severe congestion problem (The Forum of Municipalities, 2008), especially in the morning rush hours. The upper and lower TT boundaries were defined 1) in order to ensure that the travel time was not to short, otherwise there would be little incentive for the respondent to consider rescheduling, and 2) because appr. 95% of all commuting trips by car in the Danish National transport survey had travel time duration of less than 60 minutes during the morning peak period in the greater Copenhagen area, thus nearly all trips would be covered by this interval. Finally, as mention in the beginning, we predefined a set of groups to which respondents were assigned to the group who were closest to their own travel characteristic. In our case we predefined groups with travel time intervals of 10 minutes, hence we defined six different groups of TT=10, 20, 30, 40, 50, and 60 minutes. Based on these predefined groups, we built six different efficient designs accordingly.

4 Balancing the design

Once the alternatives, attributes, levels and the prior parameters have been defined we can start building the design. The design is constructed through an iterative process which follows the following steps:

0. **Define initial starting values**: the levels and priors are defined (discussed in section 3).
1. **Generate design**: this process generates the experimental design
2. **Simulate choices**: this process creates hypothetical choice sets, which is used to test the design
3. **Estimate parameters**: based on the synthetic datasets we estimate the model parameters
4. **Evaluate performance**: finally, the estimated parameters are compared to the prior parameters
    a. If the design meets the requirement (e.g. prior parameter can be recuperated), then stop.
    b. Else, adjust the levels and/or the prior parameters and go to step 1.

To ***generate*** the design we used the software package Ngene (ChoiceMetrics, 2012b). We constructed a D-efficient design using a RSC (Relabelling, Swapping and Cycling) algorithm[1]. Since we are using non-zero priors we compute the *D-error* as follows (Rose and Bliemer, 2009):

$$D_p\ error = det\left(\Omega_1\left(X, \hat{\beta}\right)\right)^{1/K} \tag{9}$$

Where Ω_1 is the asymptotic variance covariance matrix of dimension *K* x *K* as a function of the experimental design, *X*, and the prior parameters, $\hat{\beta}$, while *K* is the number of parameters. A small *D-error* denotes an efficient design. We ran the software until no noteworthy improvement occurred for the *D-error.* This was done for all six designs (TT = 10-60 min). Afterwards, we ***simulated*** the choice by calculating the systematic utility using the prior parameters, and drawing identical and independently distributed (i.i.d.) random error terms from an extreme value (EV) type 1 distribution. The alternative with the highest probability was chosen. The design was simulated using appr. 18,000 observations. We then ***estimated*** the parameters using the simulated choices. The estimation was done using PythonBiogeme (Bierlaire, 2003; Bierlaire and Fetiarison, 2009). Finally, when ***evaluating*** the design, we calculated the ratio and t-test for the estimated parameters

[1] The RSC-algorithm was applied using the following settings: swap(random=500, swap=1, swaponimprov=40, reset=10000, resetinc=5000)

against the prior parameters. Furthermore we verified that the micro-economic conditions are fulfilled and that $0 > \beta_{SDE} > \beta_{SDL}$, which according to previous studies should be expected. After testing a wide range of designs and numerous adjustments a final design was reached in which the true parameters could be recuperated and the size and magnitude were as expected. Table 3 shows the evaluation of the final designs against the priors, while table 4 shows the level values used in the designs.

	Estimation results of final design			Scaled	Prior		t-test
Parameter	Coefficient	Std. error	t-test	parameters[2]	parameters	$\widehat{\beta}/\beta$	against β
β_{ETT}	-0.011	0.003	-3.760	-0.009	-0.012	1.341	1.005
β_{TC}	-0.017	0.003	-5.120	-0.014	-0.018	1.312	1.245
β_{ESDE}	-0.013	0.002	-7.720	-0.010	-0.008	0.795	-1.232
β_{ESDL}	-0.015	0.002	-9.400	-0.011	-0.012	1.080	0.583

Table 3: Evaluation of the final designs against the priors.

Attribute	Unit	Levels			
		1	2	3	4
Departure time change - early	[min]	-15	-30	-45	
Departure time change - late	[min]	15	30	45	
TT - early & late	[%]	70	80	90	
TTV - TT 10 & 20 min	[min]	3	6	9	
TTV - TT 30 & 40 min	[min]	5	10	15	
TTV - TT 50 & 60 min	[min]	10	20	30	
TC - current	[DKK]	16	19	22	25
TC - early & late	[DKK]	7	10	13	16

Table 4: Level values used in the final design.

5 Questionnaire

After finalizing the SP design, we needed to construct the remaining of the questionnaire. For that we relied on a heavily modified version of the Danish National Transport Survey (TU) (Christiansen, 2012; Christiansen and Skougaard, 2013). This was decided in order to utilize the experienced gained through collecting data in a Danish context. The questionnaire built for this study was structured in six phases:

1) **Introduction and some initial questions**. After a brief introduction on the scope of the study, respondents were presented with some questions (in particular their preferred arrival time and their home and work location) which allows us to customize the remaining of the questionnaire.
2) **Full trip/activity diary.** Respondents were then asked to describe the trips performed during their last working day. This part of the survey was based on the TU survey trip diary (Christiansen, 2012) that contains detailed information on all trips and activities (also the ones with very short duration), such as transport mode, departure time, travel time, and purpose of the trip, and if the trip was performed alone or jointly with other people.
3) **Flexibility of each trip reported in the diary**. In addition to the traditional (in the departure time studies) information about fixed/flexible working hours, we also included a set of highly specific question to specifically capture the flexibility constraints for each trip in the trip diary. These questions aimed to capture potential (often not conscious) constraints in the departure time that are not revealed by the typical question(s) regarding whether the work is flexible or not. For more information see Thorhauge et al. (2015a).
4) **Stated preference experiments**. Based on the information reported in phase 1 and 2, the customized Stated Preference (SP) experiment described in the paper was presented to the respondents. Individuals were asked to choose among three departure times: the current departure time and an earlier or later departure time as shown in Figure 1.

[2] The synthetic dataset were generated assuming a scale of 1.28 in the error term.

5) **Indicators for latent constructs.** A set of 24 statements (ranked on a 1-5 likert scale) were used to define 8 latent constructs according to the Theory of Planned Behaviour (Ajzen, 1991). The latent constructs are *Intention*, *Attitude* (towards short travel time, being flexibility, and being on time), *Social Norm* (SN), *Personal Norm* (PN), *Perceived Behavioural Control* (PBC), and *Perceived Mobility Necessities* (PMN). For more information see Thorhauge et al. (2015c).
6) **Socio-demographic information** about the respondent and her/his family. For all the household members we collected: age, sex, income, household position (e.g. father/mother), and if they have a driver's license. For the person interviewed we also collected: level of education, occupation, work location, if they have bike and/or season ticket, parking facilities at work, possibility to work from home (number of days within the last month), working hours per week and whether these are fixed or flexible. Finally, we collected a few household characteristics: household location, household composition, parking facilities at the household, and number of cars in the household.

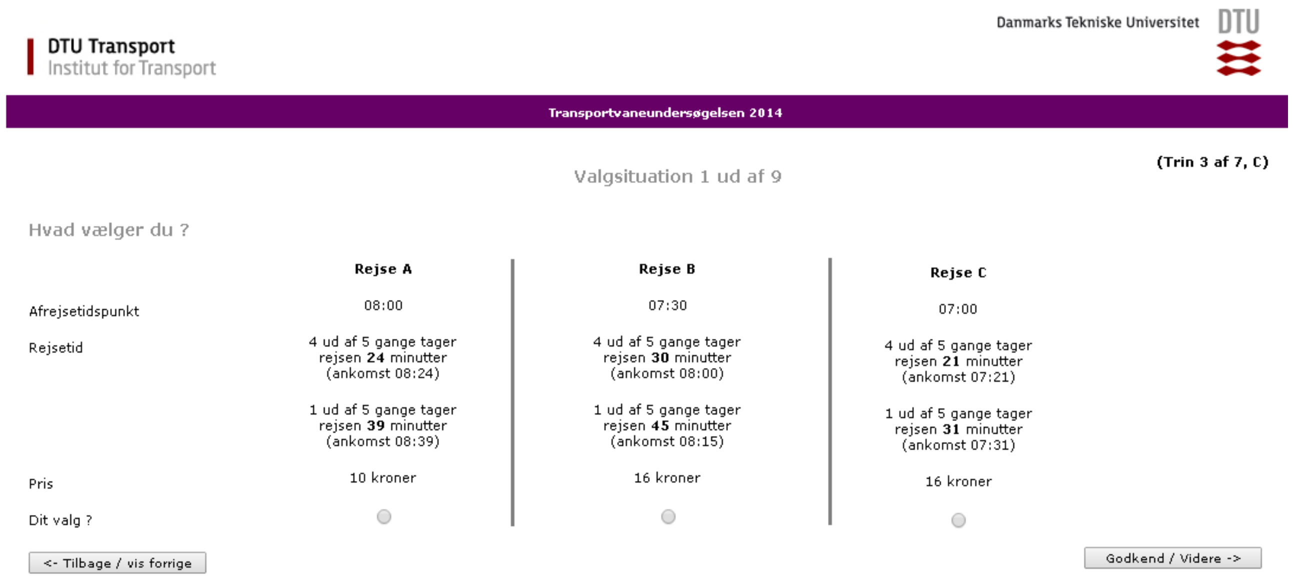

Figure 1: example of a choice task for a respondent with preferred arrival time 9:00.

It is important to note that the SP exercise was presented within the trip diary; i.e. as soon as a work trip was registered in the trip diary the respondent was presented with the SP choice experiment for that specific trip. The questionnaire was designed in this way in order to present the choice situation as early as possible in order to make sure that the respondent still has the actual trip and – more importantly – the actual constraints fresh in mind. After having completed the SP, respondents were asked to continue the trip diary.

The questionnaire was designed as an online survey. The main advantages of using a web based questionnaire is that 1) it allows to easily construct customized questionnaires (which is important due to realism) with conditional questions for each respondent based on their specific trips and socio-economic characteristics, 2) the cost per interview is relatively small, which allows for a larger sample size with limited resources, 3) it allows to define a set of criteria to be fulfilled by the people within the internet panel, and in that way ensure that only people who is in our target sample is present in the final sample, and 4) it allows respondents to answer the questionnaire when they have time, thus we hope to achieve a high(er) answer-rate. The disadvantage is that some groups of society (who do not use computers, e.g. kids and elderly people) are not present in the survey. However, since this study is limited to work trips in the rush hours, neither kids nor elderly people will be in the target group. For more details regarding the questionnaire and the sample we refer to Thorhauge (2015b; 2015c; 2015d).

6 Discussion & concluding remarks

For this study we designed an efficient stated preference experimental design for departure time choices for morning car commuters. The experimental design included three departure time alternatives: an early and late departure time option, and a departure time which are close to their current. The two most challenging aspects of generating stated choice experiments for departure time choices are 1) obtaining realism, and 2) dealing with interdependencies among attributes. To ensure realism we used a pivot design using their current travel times as a reference. It can however be argued that using the TT reported by the respondents is not ideal, since individuals often have a tendency to overestimate the time spend travelling. However two main steps are believed to minimize such an effect. Firstly, a control feature was built into the questionnaire, comparing length travelled with the reported time, thus prompting the respondent to verify or reconsider the reported travel time if the average speed was found to be unrealistic. Secondly, since we wanted to perform a 1-step data collection, we pre-defined six groups with specific travel characteristics ranging from TT=10-60 minutes with 10 minutes intervals between the groups. The respondents were then assigned to the group to which they were closest, thus the reported TT of the respondents were not used directly to generate the designs. The interdependencies among variables was dealt with by carefully selecting the level values, thus ensure that rescheduling would reduce TT, while at the same time define an interval of interest during the morning rush hours for the target group, thus ensuring that the respondent was actually facing congestion in their current departure time slot. We defined that respondent should currently arrive at work between 7:00-9:00 AM, and travel towards the city centre.

The benefit of building an efficient design is that the experimental design is tailored specifically to the model specification, and thus improving the parameters estimation. The downside is that the design is less flexible in cases where the model specification and true parameters are not known or little information available about the true parameters. More specifically, one of the most critical aspects of constructing efficient designs is to obtain prior parameters which are close to the true parameters, which can be a difficult task. However, for departure time choices the scheduling model have almost become the standard approach, hence a number of studies were available to hint about the true parameter. It is difficult to say if the efficient design performs better than a similar orthogonal design would have taking into account the additional time and effort needed to create the efficient design. However, we note that overall we managed to construct an efficient design, and recuperate the prior parameters. The t-tests of the estimated parameters were not statistically different from the prior parameters at 95% confidence. For more on the performance of the presented experimental design and modelling estimates we refer to Thorhauge et al. (2014; 2015a; 2015b; 2015c).

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