

Behavioural Responses and Network Effects of Time-varying Road Pricing

Dirk van Amelsfort

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Behavioural Responses and Network Effects of Time-varying Road Pricing

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January 2002 I started my PhD research which now results in this thesis. Six years that I have enjoyed, but I have also struggled at times. It turns out that I like doing the research more than I like writing about it. Especially when trying to finish a thesis this not the best preference to have. Fortunately I have been supported in my struggles, as well as my enjoyments, by a great number of people.

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PART A: Road Pricing Introduction

This thesis addresses road pricing from a traffic engineering perspective, focusing on behavioural responses and network effects. The overall objective of this research is to develop a pricing impact model capable of forecasting the changes in car network performance given a time-varying road pricing measure.

This part covers:

- The research objectives, research scope, and research approach. This thesis will cover the research in three other parts. In Part B, research on behavioural responses to road pricing is presented. In Part C, the road pricing impact model is developed. In Part D, overall conclusions and recommendations are discussed
- Discussion on policy objectives of road pricing in which four objectives are distinguished: internalisation of external costs, solving traffic problems, financing infrastructure, fairer transport system.
- Discussion on the primary and secondary design dimensions of road pricing measures. Primary design dimensions are: price level, differentiation level by place, time, user groups and vehicle types. Secondary design dimensions are: information provision, identification, charging, payment, and enforcement systems.
- The development of a stimulus-response framework in which the relations between road pricing stimuli, behavioural response of travellers and subsequent system changes are detailed, along with different feed-back mechanisms

1 Introduction

The transport of people and goods is important to the economic development of regions and nations. In most cases, the transport of individuals can be seen as derived demand, which means that the transport is not a purpose in itself, but a necessary means to engaging in an activity at another location. It is desirable that people engage in activities of their choosing, but the resulting transport does have negative effects on society. The significant growth in car traffic, especially, has negative effects such as environmental pollution, noise pollution, congestion, and less attractive public spaces. The challenge for governments is to manage mobility in a way that allows people to continue to engage in their desired activities while minimising the negative effects of transport. One of the policy options governments use to manage mobility is road pricing.

According to Wikipedia, road pricing is: "...an economic concept regarding the various direct charges applied for the use of roads. The road charges include fuel taxes, licence fees, parking taxes, tolls, and congestion charges, including those which may vary by time of day, by the specific road, or by the specific vehicle type, being used....". An important component of any road pricing definition is that travellers somehow pay for travelling. Some definitions do not specify that travellers pay for the use of a road, thereby suggesting that general car ownership taxes are a form of road pricing as well. In this research, we define road pricing as follows: "Road pricing is a policy tool in which car users are charged instantly for using a road or road infrastructure in an area. The traveller is charged at the time of use of the road (or area), where the charge may vary by time of day, specific road and vehicle type." This definition excludes general car ownership taxes and fuel taxes as road pricing measures, but allows for toll roads, cordon charging and kilometre charge measures.

Pricing of mobility and trips is not a new policy instrument. It has, for example, been very successful in controlling parking in inner cities all over the world. In the Netherlands, toll roads go back to at least the 17th century. Figure 1.1 shows, for example, a toll booth established in 1633 to finance the construction and maintenance of a road between Overschie and Schiedam.



Figure 1.1: Toll booth between Overschie and Schiedam established in 1633 [source: 10396 - De Schatkist van het Rijk, Belasting & Douane Museum, Rotterdam]

The construction and maintenance of infrastructure in the Netherlands is today being paid for by a system of taxes on the ownership and use of cars. Broadening the scope somewhat, travellers consider it normal to pay for train or plane tickets. No traveller is surprised that the cost of a taxi ride depends on the travel time and/or travel distance. In essence, one could conclude that pricing of mobility has always been around and will always be around, simply because the construction and maintenance of infrastructure comes at a price. The construction and maintenance of infrastructure is, however, not the only possible objective of road pricing, as we will discuss later.

This thesis addresses road pricing from a traffic engineering perspective. This means that, given different policy objectives, we are interested in the behavioural responses of travellers and the resulting changes in the performance of the transportation network. The behavioural responses relate to the travel decisions people make, like route and departure time choice. The network effects can, for example, be described by changes in flows and travel times on different roads. This traffic engineering perspective is important because most discussions about road pricing arise from the perceived lack of adequate transportation system performance. Road pricing as a measure to relieve traffic congestion during peak hours is a particularly widespread topic of discussion among policy makers. When looking at implemented road pricing measures around the world, one finds that they are all implemented with the aim of improving network performance rather than optimizing from a welfare-economic point of view.

The policy issue of road pricing is typically a problem concerning very many different aspects of daily life, not only travelling as such. While tolling often firstly aims at influencing driver behaviour, it has many other impacts. Because travel costs will change, travellers may decide to adapt their home or work locations in order to reduce the increased household expenditures.

Equally, firms may reconsider their current locations in order to prevent their employees and clients from increased transportation costs. Such processes imply that road pricing may lead to shifts in the spatial distribution patterns of households and firms which in turn may lead to shifts in spatial travel patterns. Another important aspect of road pricing is the induced money streams of toll revenues: how will these revenues be used, for what purposes, and with what potential impacts? Since a net positive revenue is not at all secured, because of the high investment and operational costs of such systems, a serious question in each particular toll system proposal concerns the financial viability of the proposal. Another relevant policy concern is the acceptance of some form of road pricing by the general public: in the public there maybe conflicting opinions about the use of the revenues, the social equity of the tolling measures, the privacy of the tolling data, the effectiveness of the proposed measures, etc.

Designing road pricing measures such that they meet policy objectives is a complex task, even when neglecting the social and political environment in which the decision making takes place. Issues arise about the rationale and objectives of road pricing, where multiple objectives may be formulated that support or contradict each other. One of the key issues in designing road pricing measures is the anticipation within the design of the behavioural responses of different actors and of the system changes.

In order to shed more light upon these interrelated road pricing issues, a consortium of Dutch universities has, in 2002, launched a multidisciplinary research program called MD-PIT: Multi-Disciplinary Study of Pricing in Transport. This ongoing program is being sponsored by the Transportation program (VEV) of the Dutch National Science Foundation NWO. The purpose of this program is to study a variety of road pricing issues from various relevant perspectives such as the traffic engineering perspective, the economic perspective, the psychological perspective, and the geographical perspective. This thesis is part of the traffic engineering subprogram of MD-PIT. For details about the other subprograms and projects of MD-PIT we refer to Steg et al. (2006) and sources given therein.

In the traffic engineering part of MD-PIT, three major streams of studies have been performed in co-operation with the other involved disciplines:

- conducting a large scale survey aimed at collecting stated preference data on travel decision making by individual travellers in response to road pricing measures, and deriving from these responses a set of crucial parameters describing the choice behaviour of travellers in case of road pricing such as price sensitivity, value of travel time, value of schedule delays, value of travel time reliability, and the like;
- based on the collected data ad a., development of a set of travel choice models for use in a comprehensive dynamic network flow prediction tool suitable for analyzing travel demand and traffic flow impacts of road pricing proposals;
- developing and applying a design tool for optimizing the system set-up (locations, periods, levels of the tolls to be levied, etc) of road pricing regimes in dynamic networks.

Again, when looking at road pricing from a traffic engineering perspective, we want to know where, when and how traffic patterns change and how this contributes to the policy objective. In order to assess the effectiveness of road pricing from a traffic perspective, quantitative analysis tools (models) are needed that forecast the likely impacts of particular forms of road pricing as a means to solve particular problems as expressed by policy objectives. These modelling tools for analyzing given pre-specified road pricing schemes are called *road pricing impact models*.

Apart from such tools, which are able to predict the likely consequences of proposed road pricing measures specified in advance, one may think, one step further, of quantitative tools (models) that may derive the best charging pattern to be applied given a specific policy objective. We call this type of modelling tool a *road pricing design model*, since it is able to determine the optimal combination of characteristics for a toll regime, consisting of where, when, from whom, and how much toll to levy (see Joksimovic (2007)).

Together, the road pricing impact model and the road pricing design model address the network design problem, offering policy makers the opportunity to change the design variables of the transportation system. These changes will affect the behavioural responses of travellers and as a result the performance of the transportation system. Policy makers will then evaluate the key performance indicators (KPI's) of the transportation system and possibly make new adjustments to system design variables. This interactive process is presented in Figure 1.2.

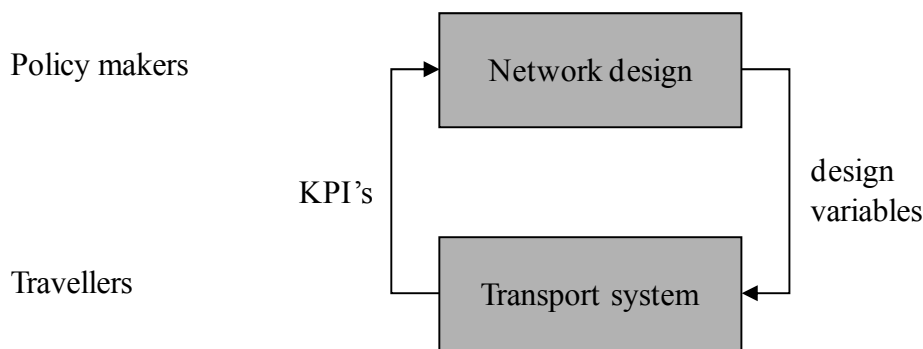


Figure 1.2: Network design problem

In this thesis, the *road pricing impact model*, which is contained within the bottom part of Figure 1.2, is developed. At this level, the direct behavioural responses of travellers to the road pricing stimulus and the indirect responses of travellers as a result of system changes interact (see Figure 1.3). The *road pricing impact model* developed in this thesis consists of three components:

- modelling the behavioural responses of travellers;
- modelling the flow of traffic through the network;
- modelling the interaction between behavioural responses and traffic conditions (equilibrium aspects).

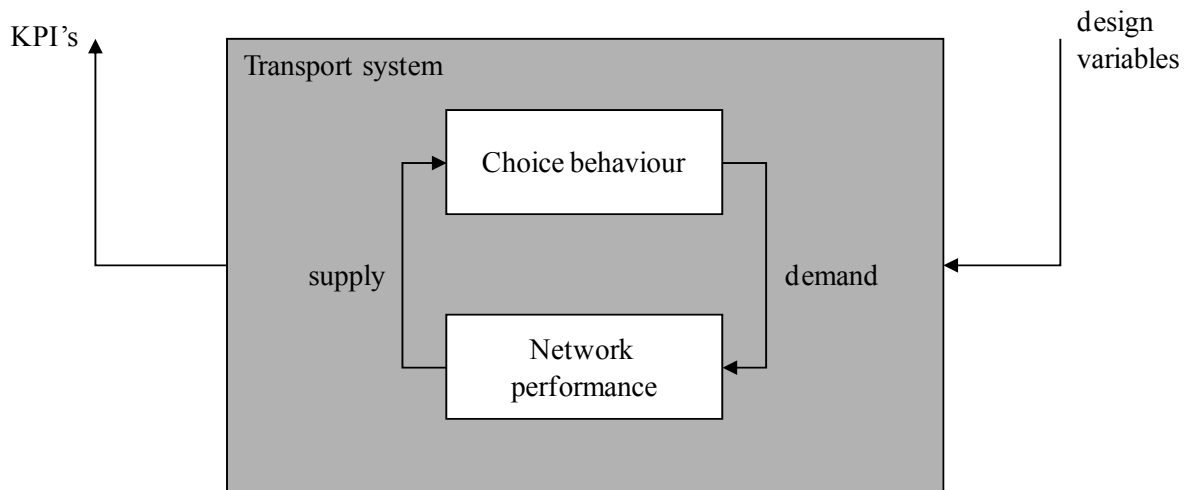


Figure 1.3: Individual choice behaviour and available infrastructure determine performance of transport system

Key contributions of this thesis

The first contribution is that we established a new comprehensive stimulus-response framework that describes in detail how road pricing measures may affect the actions of individual travellers, how travellers may adjust their travel behaviour, and thus consequently affect the transport, economic and social systems. A wide gamma of potential reactions of different actors (individuals, households, companies, etc) is included in this framework. As a consequence of resulting changes in the transport system, further behavioural responses are considered. The stimulus-response framework firstly provides insights and an easy understanding of how road pricing directly and indirectly may affect individuals and the transport system. In addition to this, the framework constitutes a set of hypotheses on stimulus-response behaviour that are tested with new dedicated empirical data and advanced travel choice models. The framework is also the basis for operational impact models with which network wide effects of road pricing measures can be assessed.

Secondly, based on the theoretical framework, a unique dedicated empirical data set has been established using a stated choice experiment with the purpose of gaining insights into commuter's responses, testing of pertinent hypotheses and estimating behavioural parameters. The stated choice experiment includes commuter's route, departure time, and mode shifts in response to time and place differentiation of road pricing stimuli. Additionally, the data include travel time unreliability as a traveller's choice attribute with a new way of operationalisation in order to better represent the unreliability experienced in real life.

Thirdly, and from a methodological perspective, we respect the repetitive nature of the commute trip in the stated preference experiments by having respondents distribute a given number (10) of trips among alternatives rather than making a single choice. This innovative approach demonstrated that respondents appear more sensitive to road pricing and are more likely to change departure times than is shown in traditional stated choice approaches.

The fourth and major contribution of this research is the establishment of a range of extensive departure time choice models for the sake of hypotheses testing and parameter estimation. These models of the random utility discrete choice type are characterized by a wide spectrum of potential and partly new explanatory variables in their utility functions. Traditionally,

departure time models that use a scheduling approach only consider variables at the arrival side of a trip. Our new models relax this limitation by considering, for the first time, variables (various forms of early and late scheduling delays) at both the departure and arrival sides. It appears that both sides contribute significantly to the trip costs and that there exists non-linear sensitivity of travel costs towards trip rescheduling. The models show, for example, that commuters may not mind arriving somewhat later at work than preferred, as long as they leave home at their preferred time. We could also demonstrate that commuters may be able to adjust departure times within limits and that rescheduling departure or arrival outside periods incurs further travel costs upon the traveller. Whereas in literature the role of travel time unreliability has been tackled using either a mean-variance or a scheduling approach, we have shown that a combination of both performs better. While under some conditions the two approaches have been shown to give identical results, it appears that a separate unreliability parameter can also be significant in a scheduling approach.

A fifth and final important contribution of this research is the establishment of an operational state-of-the-art, analytical, multi-user class dynamic equilibrium modelling framework which apart from route choice includes both departure time choice and elastic demand. This set of models allows for the estimation of the network-wide travel and traffic impacts in response to a wide range of (dynamic) road pricing measures. There exist only very few comparable model structures, which in most cases use a simulation approach or some heuristic models which, from a research perspective, is less attractive. Most modelling frameworks are, however, much more simple; they are either not dynamic, do not include departure time, elastic demand or both and thus are in essence incapable of forecasting network effects of time-varying road pricing measures. The modelling framework has been shown to be feasible on large scale networks and has even been shown to be applicable even within a road pricing optimisation framework (not covered in this thesis).

1.1 General research objective

The main objective of this research is to develop a *road pricing impact model* that is capable of assessing where, when and how traffic patterns change given a specific planned road pricing measure. We look at road pricing from a traffic engineering perspective, which means that we are mainly interested in road pricing measures with the objective of improving traffic conditions and we will assess the effects of road pricing measures on the traffic systems in traffic engineering analyses, such as travel times, flows, etc. Since traffic problems do not occur everywhere, or always at the same time, or in such a way as to affect all travellers in the same manner, we are interested in road pricing measures that may be differentiated by any of the primary design dimensions. Given our traffic engineering focus we are mainly interested in those behavioural changes that directly affect the performance of the car traffic network, such as changing levels of car travel demand, departure time and route choice changes.

The research in this thesis thus needs to contain two important components, namely: 1) research into behavioural responses, and 2) research into determining traffic conditions, including feedback with choice behaviour. We discuss research on different aspects of these two components in more detail in the succeeding section, after which we formulate research questions and a research approach.

1.2 Research on route, departure time and mode choice

Many have researched the topic of road pricing, from various professional perspectives and with varying objectives. In order to determine our research approach from the presented

research question, we first present a concise review of the literature on both the behavioural responses and the assessment of network effects, in order. From the literature review, we can identify interesting fields of research for our approach.

1.2.1 Route choice

Depending on the road pricing measure, it may be more economical for commuters to divert to alternative routes. The extent to which commuters divert to other routes depends on the differences in prices on the alternative routes, as well as on differences in other attributes. The travel time of a route is always part of a route choice model, but as traffic conditions worsen, a generic travel time attribute may be split up into, for example, a free-flow and a congested travel time. For example, Hensher (2001) found that commuters are more sensitive towards stop-start traffic than slowed down traffic and free-flow traffic respectively. In recent years, different studies have also shown that travel time unreliability can be an important attribute in the choices travellers make, for example Brownstone et al. (2003), Brownstone and Small (2005), Hensher (2001), and Small et al. (1999). Other attributes have been found to be important in route choice as well, such as the number of signalised intersections on a route, the number of left-turns in a route, the comfort and/or scenic value of routes are included (for example Hamerslag (1981) and Ben-Akiva et al. (1984)).

Transport for London (2004) reports that there is no evidence of systematic increases in traffic on local roads outside the charging zone, during charging hours, in response to the introduction of the charge. Ramjerdi (1995) also reports that no significant route changes occurred as a result of the tolls on the ring road in Oslo. Eliasson et al. (2008) report a 0-4% increase in traffic on an important route alternative (Essinge bypass) around the cordon in the Stockholm congestion charging trial. Thus, although it will depend on the charge levels, cordon design, and network topology, the route effects of some important cordon charging schemes that are currently implemented seem rather small. These cordon charging measures were, however, not specifically designed to affect route choice, and perhaps route choice around the cordon could even be considered an undesired side effect.

In this research, we will assume that the route changes resulting from road pricing are the effect of a trade-off between travel costs and travel time alone, and we are interested in addressing different time and cost components separately.

1.2.2 Departure time choice

In looking at the commuters' departure time choice, we first consider a situation in which there is no congestion and travel times are completely reliable. In that situation, commuters may choose to leave for work depending on three attributes: 1) the time they are required by their employer to start working, 2) personal and household constraints, such as taking children to school, and 3) the free-flow travel time. If there is no firmly designated time at which work begins and there are no household constraints, commuters become more indifferent towards choosing a specific departure time. In essence, a commuter has a preferred arrival time (PAT) or a preferred departure time (PDT), depending on the dominating constraints, and these are linked by the free-flow travel time. This is shown in Figure 1.4.

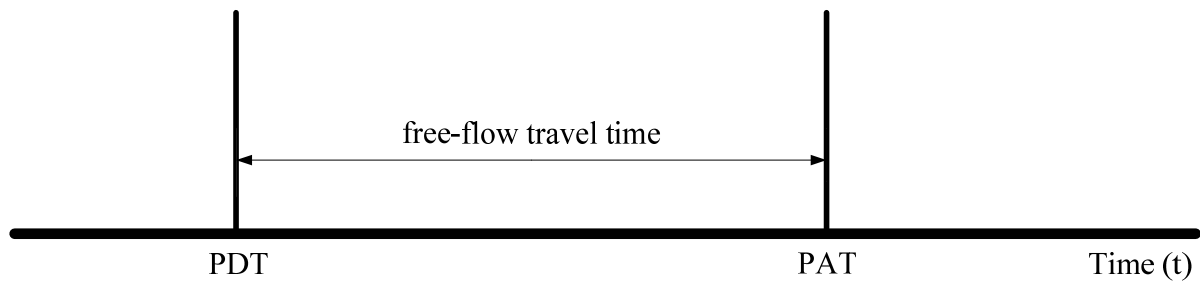


Figure 1.4: Departure time choice without congestion

Now let us consider the case in which congestion occurs. As a result of congestion, the expected travel times increase and travel time becomes unreliable. Since, on average, travel times become longer, commuters have to adjust their departure time in order to increase the probability of arriving at the same time as before, in the case with no congestion. If and how much a commuter will adjust his or her departure time depends on personal circumstances, the levels of congestion, and subsequent levels of travel time variability. In Figure 1.5, we added the effect of congestion to Figure 1.4 in such a way that the traveller, on average, arrives at the destination at his/her preferred arrival time (PAT). In Figure 1.5, ADT represents the Actual Departure Time and $E(AAT)$ the Expected Actual Arrival Time.

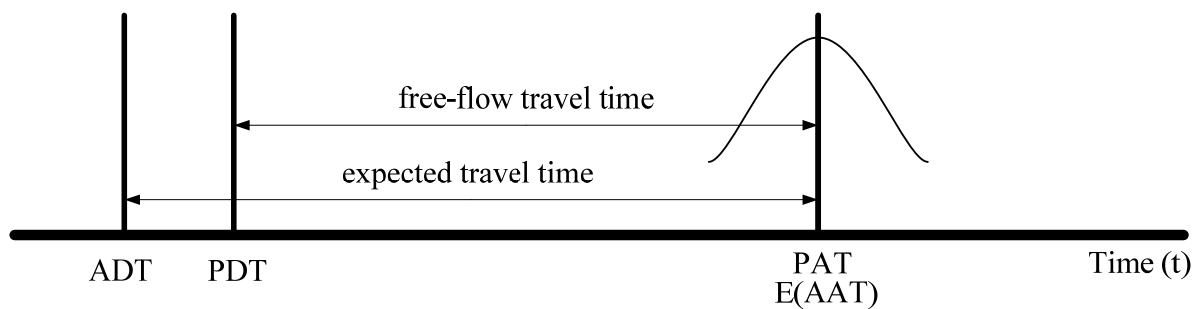


Figure 1.5: Departure time choice with congested unreliable travel times

By changing the actual departure time in order to arrive (on average) at the preferred time, the traveller has rescheduled his/her trip in anticipation of a certain amount of congestion. In research into the departure time choices made by travellers, the amount of rescheduling a traveller has to take into account in choosing a departure time has been found to be an important attribute. Becker (1965) first discussed the planning of activities from an economic productivity and consumption perspective, while the rescheduling of trips before a bottleneck was first discussed by Vickrey (1969). From these and other studies, Small (1982) addressed the scheduling of trips and used scheduling delays to explain the departure time of a traveller. The scheduling delays are often defined as the difference between actual and preferred arrival times and have frequently been used by many other researchers, for example by Small (1982), Wilson (1989) and Hendrickson and Plank (1984). We will refer to this line of research with scheduling delays as the scheduling approach. Hendrickson and Plank (1984) investigated the arrival time scheduling delays and found significant non-linear sensitivities towards rescheduling. Figure 1.6 shows the non-linear sensitivities found by Hendrickson and Plank. On the horizontal axis, the amount of rescheduling (in minutes) is displayed. Negative values represent early arrival. On the vertical axis, the utility (unit less) associated with a scheduling delay is given.

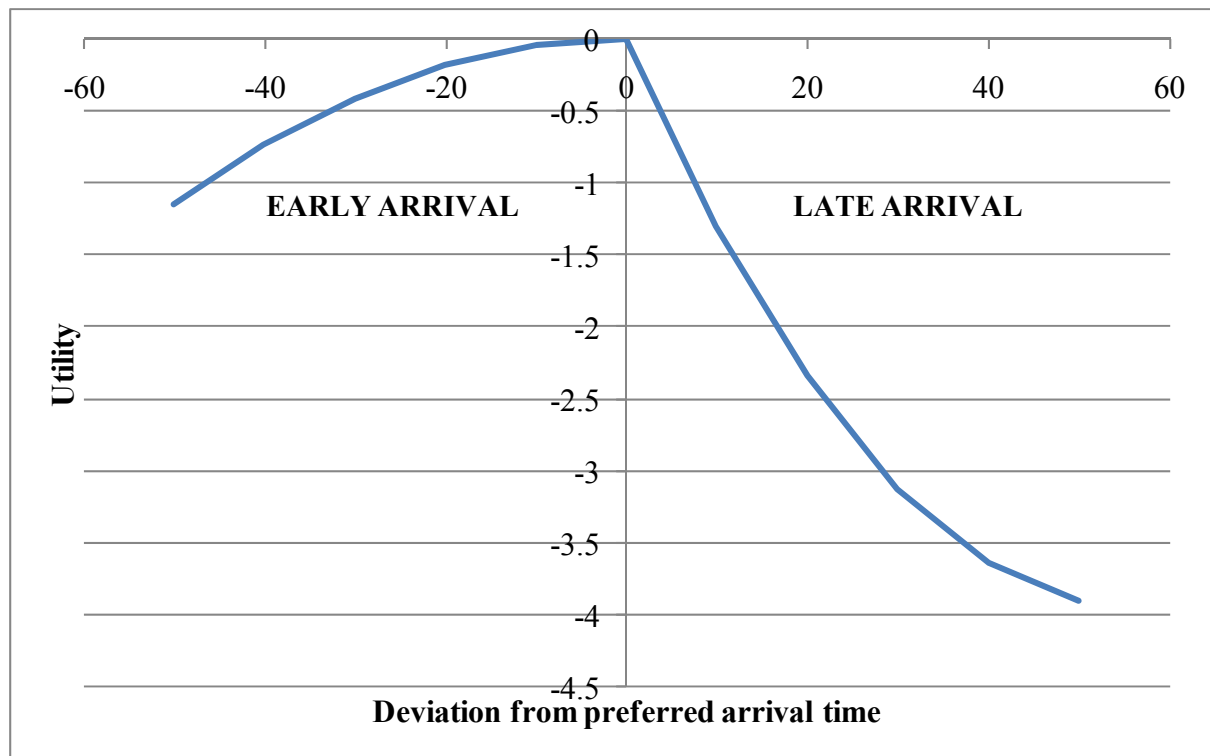


Figure 1.6: Sensitivity to arrival rescheduling found by Hendrickson and Plank (1984)

In most applications of the scheduling approach, the scheduling delays are calculated based on the average travel conditions. This neglects the potential effects of travel time unreliability on departure time choice. Noland and Polak (2001), Noland et al. (1998) and Small et al. (1999) are examples of researchers who have included travel time unreliability in a scheduling approach by using expected travel times and expected scheduling delays. Also, travel times in congested conditions change from day-to-day, and an approach using the average travel conditions may then neglect the day-to-day variance in departure time. Mahmassani and Chang (1985) and others analyse this and describe the processes by which commuters' daily departure-time decisions respond to experienced traffic conditions. The acceptability of a given decision on a given day is represented by an indifference band of tolerable schedule delay, which varies across individuals and shifts in response to individual experience. In all cases, we found scheduling delays were calculated based on deviations from the trip's preferred arrival time, while in principal rescheduling may occur from both the preferred departure and arrival time.

A completely different approach to looking at the commuters' departure time choice is to look at traffic as derived demand: engaging in an activity at another location is necessary. The decision to travel, and then the subsequent decisions on how, *when* and where to travel, depends, amongst others things, on the desired end time of the current activity and the desired start of the next (desired) activity at the (desired) location. An alternative to the scheduling approach is then the investigation of the commuters' activity choice processes, specifically the planning of activities as was, for example, researched by Axhausen and Gärling (1992). This activity based approach is being used by various researchers and Timmermans and Zhang) provide a concise overview of recent developments.

The tour-based approach is a third approach which is somewhat in between the scheduling and activity approaches. A tour-based approach models the duration and scheduling of fixed activity patterns. It does not fully explain the choice behaviour on activities, but given certain

activities patterns, the duration of activities are modelled and, as an important part in that process, the departure time for trips. A tour for a single work activity consists of an outbound trip to work, duration of the work activity and the inbound trip back home. If a commuter leaves home earlier in the morning and the duration of the work activity is constant, he/she will leave earlier to go home as well.

Departure time choice and road pricing

Beser Hugosson et al. (2006) and Karlström and Franklin (2008) found that departure time adjustments as a result of the Stockholm congestion charging trial are negligent. Overall, 65% change their departure times by less than 15 minutes or not at all. Börjesson (2008) used a scheduling approach on both revealed and stated preference data from the Stockholm congestion charging trial to model the departure time choice adjustments from the Stockholm congestion charge trial. The RP models show different sensitivities towards rescheduling than the SP models. Börjesson concludes that this is due to the temporal difference between the RP and SP data, with the SP data focused on the short term and the RP on a longer term and repeated choice. Börjesson:

The actual departure time choice is an outcome of a long-term behavioural adaptation to traffic conditions and scheduling constraints. Meetings and other temporal constrained engagements were settled with respect to this. In the SP choice context, however, the decision was more short-term since only one particular morning is considered. If a meeting was fixed, the traveller was less flexible in the departure time choice the particular morning we asked about. If the traveller had known about the travel conditions in before hand, it might have been possible to arrange the meeting at a different time. Flexibility would thus be larger in the long-term choice. Flexibility can, for other travellers, be larger in the short-term choice. It seems plausible that some respondents could be willing to depart considerably too late or too early one particular morning, which is the choice we analyse in the SP context, but less willing to make this alteration on a regular basis.

Polak et al. (1993) developed a trip timing model using a tour based approach with the purpose of forecasting the effects of alternative road pricing measures for London. They find that commuters appear highly sensitive to changes in the timing of a tour, but are relatively less sensitive to changes in the duration of the work activity. For business travel, it seems unlikely that the timing of travel would be affected by realistic levels of road pricing charges. Also, some non-linear sensitivities towards tour timing and duration were found.

Chin (1990) researched commuters' departure time choice changes in Singapore after the introduction of the Area License Scheme (ALS) in 1975. He used a scheduling approach in a nested structure with larger time shifts in the top level and smaller time shifts in the lower level. Besides linear sensitivities towards rescheduling, significant non-linear sensitivities (by log transformations) were also found. Chin reports that 24% of car drivers changed their departure time after the introduction of the ALS system, and also repeatedly remarks about the potential benefits of relaxing institutional constraints, such as working hours, in order to increase the efficiency of policy measures.

In this thesis, we adopt a scheduling approach to investigate commuters' departure time choice under time-varying road pricing. We are interested in researching the sensitivities of commuters towards rescheduling. We cannot dismiss non-linear sensitivities to rescheduling,

and we also need to include travel time unreliability; it is found to be important in decision-making and road pricing may affect the level of travel time unreliability as well. Furthermore, we do not a-priori dismiss the existence of both departure time and arrival time rescheduling. We will not, however, look at the day-to-day departure time choice nor will we adopt an activity approach in this thesis.

1.2.3 Mode choice

Road pricing may result in car drivers choosing travel options other than the car, which could include carpooling, the use of public transport, bicycling, and walking. As road pricing may improve travel conditions, some non-car users may shift to using the car. The choice between different modes will depend on characteristics of the mode, such as, among many others, travel time and cost. In the case of mode choice, both hierarchic and simultaneous choice models have been found significant in combination with destination choice and departure time choice. Although the hierarchy sometimes found in models is a statistical property rather than a behavioural one, it seems logical that the choice of a mode depends on the destination and on the time of travel as levels of service for public transport tend to vary by both time and space. We will not go into the extensive research on mode choice behaviour in detail here, but we highlight some studies that look particularly at mode choice changes as a result of road pricing.

Ramjerdi (1995) used data from before and after the introduction of tolls in Oslo to estimate mode choice models. For cars, the toll costs were found to be significant and people were more than twice as sensitive to the tolls as to parking costs and running costs. Having a seasonal pass for the tolls has a positive effect on car use. For public transport, in-vehicle time, walk time, wait time, number of transfers, and costs were included. Women were found to be more likely to use public transport. The sensitivity to public transport costs was found equal to the sensitivity towards parking and running costs for a car. Eliasson and Mattsson (2001) model the transport and locational effects of road pricing for a simplified mono centric city. They find that the public transport share may increase with 4-5% under an optimal charging regime. With a base average public transport share of about 30%, this is a substantial increase in demand for public transport.

Eliasson et al. (2008) find that the number of passengers travelling by public transit increased by 6% after introduction of the Stockholm congestion charging trial. Based on back-of-the-envelope elasticity calculations, they estimate that 1.5% can be attributed to changes of petrol prices and business-cycle effects, leaving 4.5% to be the result of the road toll. They were unable to confirm that the substantial efforts to improve public transport from before the start of the trial had an effect on the total number of public transport trips. That is not say that there is no such effect, but rather that, if it exists, it is too small to have been recorded in passenger statistics or in the travel habits survey conducted in autumn 2005.

Transport for London (2004) report an increase in bus use of about 38% between the first and second year of implementation of the congestion charging scheme in London. About half of the increase in bus use is believed to be a direct result of congestion charging.

1.3 Research on multi-user network effects of time-varying road pricing

The research on effects of road pricing is extensive and we will focus here on research that deals with assessing the traffic network effects of time-varying road pricing measures. Since time-varying road pricing measures are likely to have time-varying effects on network conditions, we limit ourselves to the research that uses so-called dynamic traffic network

models, rather than static models. Static models are incapable of assessing time-varying impacts of road pricing as they do not explicitly consider the passing of time as traffic moves through the network. There is a stream of dynamic models that look at road pricing, but instead of networks, they consider single roads in (extended) bottleneck formulations as first developed by Vickrey (1969). Although these studies capture the dynamic aspects of traffic and congestion, we are interested in studies that do this on a network level, rather than a single road, or bottleneck. We are thus interested in studies that model time-varying road pricing measures using dynamic traffic assignment network models.

De Palma et al. (2005), De Palma and Lindsey (2006), De Palma et al. (2004) are some examples of research by De Palma, Lindsey and colleagues on time-varying road pricing measures using a dynamic simulation model. De Palma et al. (2005) state the following in their analyses on modelling time-varying road pricing measures:

...Time-of-day pricing has yet to be analyzed on medium- or large-scale networks using a fully dynamic model. Tolling of general networks is analyzed in Carey and Srinivasan (1993) and Yang and Bell (1997), and time-of-day pricing is simulated on a road network in Hong Kong by Hau et al. (2003). However, trip timing is exogenous in these studies. Viti et al. (2003) treat departure-time choice endogenously, but their objective function includes travel time costs but not schedule delay costs. Safirova et al. (2004) study congestion pricing for Washington, DC, using a discrete-choice demand structure with multiple behavioural dimensions and a relatively detailed network specification. But their application includes only three broad time periods, and the tolls they consider are the same across time periods and freeways.

...In summary, existing studies of road pricing all lack one or more of the following elements: (1) modeling of trip-timing decisions at a fine level of temporal resolution, (2) accounting for trip-timing preferences in the welfare assessment, (3) tolling by time of day, and (4) road networks of practical interest....

In the paper, they present a modelling approach based on a microscopic traffic simulation model where the mode, departure time and route choice of individual travellers are modelled explicitly. The number of trips, destination choice and car occupancy of travellers are assumed constant. The mode choice model uses the generalized systematic cost of public transport, which is assumed to be exogenous and independent of time of day. The departure time choice model uses a scheduling approach in which travellers are assumed to have individual-specific preferred arrival time windows at their destination, and if they arrive earlier or later, they incur a schedule delay cost. The generalized systematic cost of an auto trip is additively separable in travel time costs, schedule delay costs and toll payment. Route choice is governed by a heuristic based on a generalization of Wardrops minimum-cost principle, which closely approximates the minimum generalized cost. Route choice decisions within a day are revised at road network intersections. A day-to-day adjustment process with exponential learning by drivers governs changes in mode choice, departure time and route choice, and guides the system towards a stationary state.

The model structure presented above was applied by De Palma and Lindsey on a case for Paris in De Palma and Lindsey (2006) and on a more theoretical network in De Palma et al. (2005). In the Paris case, a 10-year, 4-phase implementation strategy for road pricing in Paris was evaluated, where in the end phase cordon charges (city centre and Boulevard

Périphérique) are assumed to depend on travel times. They find that user benefits range from 1.5 to 3.5 times the reduction in external costs. Thus, savings to users in travel time and schedule delay costs account for the bulk of the welfare gains. Moreover, user benefits amount to 65–85% of toll revenues. This suggests that more than a third of the revenues were returned to users. In the theoretical network, four different road pricing measures are examined, namely: 1) system optimal pricing, 2) flat charges on almost all links, 3) flat and step cordon charges, and 4) flat and step area charges. In this study, it was found that amongst the results of the simulations, two stand out. First, for the parameter values used, step tolls generate approximately twice the welfare gains of flat tolls, while inducing a smaller shift of trips from auto to transit. Second, step tolls generate smaller revenues than flat tolls do, and consequently have more favourable distributional impacts on travellers. In both studies, the authors comment on the modelling structure and present several lines of research for further improvements, such as: regarding more travel purposes than work trips in the analyses, include more aspects of heterogeneity in choice behaviour (travel time, scheduling costs, etc), improve public transport modelling, and include land use and destination choice models.

May and Milne (2000) compared four road pricing systems, with charges based on cordons crossed, distance travelled, time spent travelling and time spent in congestion, using the dynamic assignment network model for the city of Cambridge. Charges were imposed inside an appropriate ring of bypasses. The study looks at route choice and elastic demand effects, and the departure time adjustments of travellers are implicit and assumed to be included in the elastic demand module. Also, the heterogeneity of road users is not considered in the modelling approach. They find that when rerouting effects are included in the predictive modelling process, the benefits of road pricing may be significantly smaller than previously expected. May et al. (2002) and Sumalee et al. (2005) use a similar modelling approach to optimise cordon charging schemes and find that the cordon schemes found by the optimisation schemes outperform the schemes based on the judgements of experts.

Overall, one may conclude that not so much research exists on the dynamic traffic effects of time-varying road pricing measures. There are three or so approaches available, but none of them completely cover the changes in demand, departure time adjustments and route choice. The heterogeneity in choice behaviour is not always considered to the full extent either.

1.4 Research questions and approach

1.4.1 Behavioural responses to road pricing

In order to research the behavioural responses of commuters towards time-varying road pricing, we need to know how traffic demand levels, departure time choice and route choice will change as a result of the road pricing measure. Mainly with regard to the departure time choice of commuters towards road pricing not so much is known, especially not for the Netherlands. In trying to solve traffic problems, however, the departure time responses might be of key importance. In this research we will therefore look in detail at the departure time responses of travellers towards time-varying road pricing (and other travel characteristics). The key research questions are:

- How can time and place differentiated road pricing measures affect the route and departure time choice of travellers?
- How constrained are travellers with respect to their departure time and who imposes these constraints on travellers?
- How sensitive are travellers towards travel time, travel costs, and towards rescheduling their trip when faced with time-varying road pricing?

- Have travellers got different sensitivities towards different travel cost components?
- Are travellers linear in their sensitivities towards the different attributes?
- What is the importance of travel time unreliability in departure time choices?

In order to answer the questions above we use a choice modelling approach. In this approach, we are able not only to determine what attributes are how important in the decision making of travellers, but the resulting models can also be implemented in the road pricing impact model in order to assess the network effects of pricing measures.

In order to estimate the sensitivities and significance of the different attributes we are interested in, we need data concerning the choices of individuals, wherein these attributes have changing values. Since we do not have access to these individual choice data from time-varying road pricing measures in the Netherlands, data needs to be collected. To this end, a survey will be undertaken among commuters. The route, departure time and mode choice of commuters is measured in a stated choice experiment. Using the choice data, we can then estimate parameters for each attribute and develop models that can forecast the actual choice behaviour. In the data collection we focus on commuters rather than all travellers. We realise this is a simplification of reality, but since our focus is on solving traffic problems, we can focus on congested periods and in the Netherlands the traffic in peak hours predominately exists of commuters. If we can affect the choice behaviour of (a part of) this group most traffic problems could be solved.

In the first two chapters of Part B, we will discuss the design of the survey and some of the characteristics of the respondents who answered the survey. In the succeeding chapters of Part B, the data are used to estimate different choice models, with the objective of discovering which attributes are important to the decision-making of commuters.

1.4.2 Network effects of road pricing

As we have seen in Section 1.3 there is exists only limited research on forecasting the network effects of time-varying road pricing. Most research is not dynamic in nature (it does not consider the flow of traffic through the network), it does not consider multiple user classes in the system with different prices and different behaviour, and/or it does not look at network effects but only at effects in bottlenecks or small corridors. In this research we aim to develop a road pricing impact model that combines all of these aspects in a equilibrium approach. The main research questions that arise from this are:

- How can we construct interactions between system performance and choice behaviour?
- How can we include route choice, departure time choice and travel demand changes in a single equilibrium modelling framework?
- How can we design this modelling framework so that it can be applied in practise on realistic networks and by distinguishing multiple user classes?
- Can we use develop a modelling framework that in theory can be used for optimisation of road pricing measures given a specific policy objective?

The first research question addresses the assessment of the network performance given the behavioural responses to road pricing. Since there are direct and indirect responses to road pricing, as was discussed in Chapter 2, the behavioural responses also depend on the changes in network conditions. In this thesis, we develop a model framework that explicitly models these interactions between behavioural responses and network performance, which together will result in a new equilibrium situation. In Part C, the road pricing impact model is

developed, partly using choice models from Part B of this thesis. We test the modelling framework on a small case study and then present one of the applications of the modelling framework for a reward pilot program called “Spitsmijden”, in which commuters receive a monetary reward (a negative charge) if they do not travel during peak hours between Zoetermeer and The Hague in the Netherlands.

1.5 Thesis structure

Figure 1.7 shows the overall structure of the thesis into four parts together with each of the chapters contained within a part. In the remainder of Part A of the thesis, we present our further investigations into how road pricing can be designed and how it may affect people, directly or indirectly. This results in the establishment of a stimulus-response framework which is also presented in Chapter 2. Based on these analyses, we can then focus in Part B, on the behavioural responses of commuters towards road pricing. Part B contains four chapters in which we address the research questions presented in Section 1.4.1. In order to research the behavioural responses we are interested in, we need data on individual choice behaviour. How we collected, what data is topic of discussing in Chapter 3. In Chapter 4 we then highlight some of the characteristics of the respondent from whom we collected choice data, since this we contribute to the understanding of current choice behaviour as well as model results that follow in Chapters 5 and 6. In these chapters we analyse the choice behaviour and determine sensitivities towards different attributes by estimation of different choice models. In Chapter 5 we focus on the scheduling, cost and travel time attributes, while in Chapter 6 we look specifically at the how travel time unreliability can be taken into account and we investigate how sensitive commuters are to travel time unreliability. In part C we address the research questions as presented in Section 1.4.2 and the topic is thus to determine the network effects of road pricing measures. Part C contains three chapters. In Chapter 7 we establish the modelling framework based on a set of requirements that stem from our objective to assess to network effects of time-varying road pricing measures and from looking at this from a traffic engineering perspective. In Chapter 8 we test the implementation of the modelling framework on a small test case and then apply the framework on a real case study in Chapter 9 and present the potential effects of different reward schemes between Zoetermeer and The Hague. In part D, we synthesize on the findings from each of the parts and formulate conclusions and recommendations.

In the next chapter will we now present our investigations into the design of road pricing measures (the stimuli) and how measures may affect the behaviour of individuals and the system (responses) by developing a stimulus-response framework. This framework we will use also in Part C of this thesis when we develop a modelling framework that operationalises part of the stimulus-response framework.

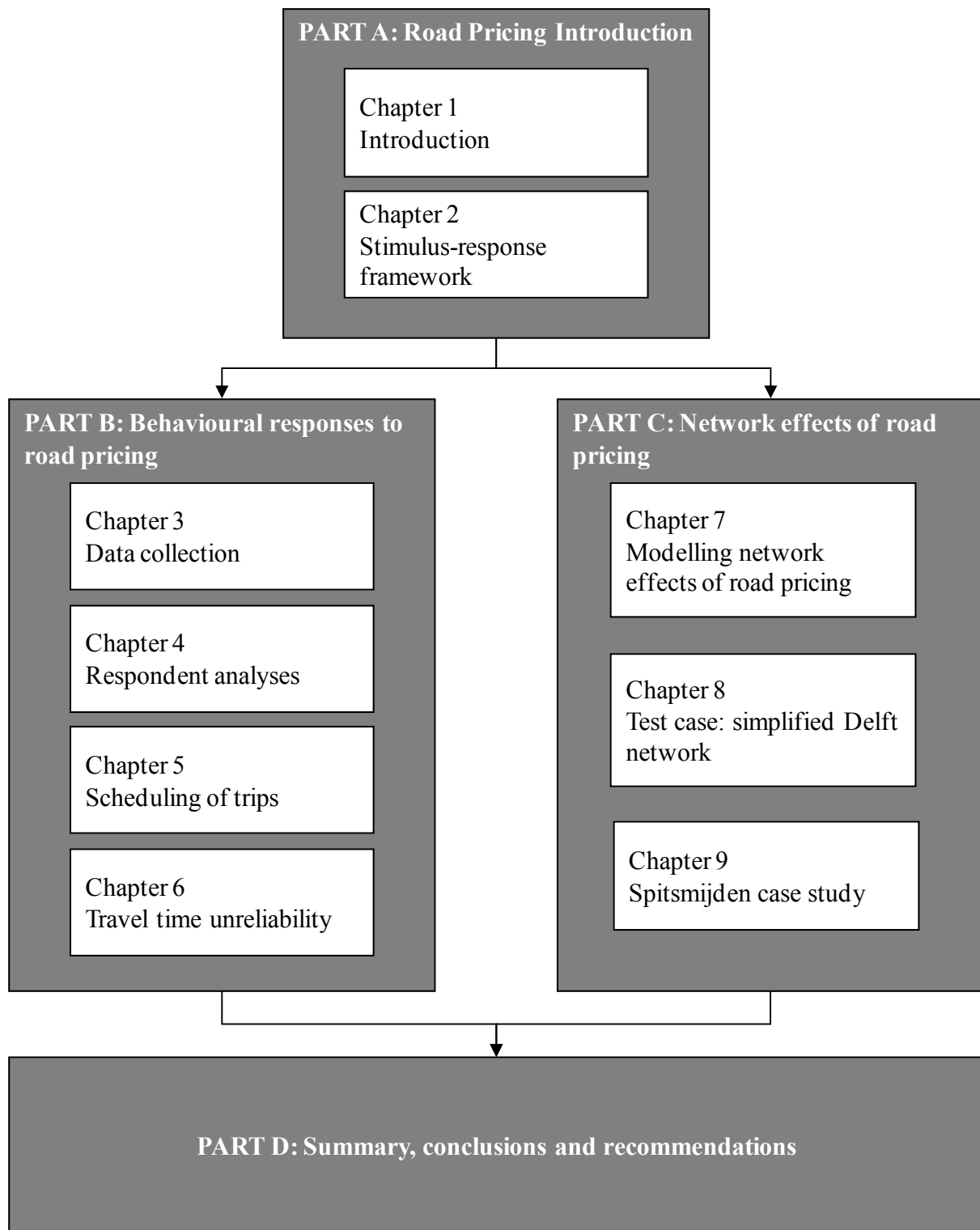


Figure 1.7: Thesis outline.

2 Stimulus-response framework

In this chapter, we investigate how road pricing may affect society. We will look at the design of road pricing measures and how this design is related to the policy objective of road pricing. Different policy objectives for road pricing are considered in this. Depending on the design of a road pricing measure, we then investigate the possible behavioural responses of different actors to road pricing.

The purpose of this chapter is to create more understanding about what road pricing is and how road pricing can affect the system. The stimulus-response framework developed in this chapter also serves as a basis for the development of the road pricing impact model. With our focus on the traffic engineering perspective of road pricing, we want to forecast the effect of road pricing on the traffic system performance by modelling the lower level of the network design problem. In this lower level, we need to know how a certain road pricing measure affects the choice behaviour of decision-makers. These relationships between the road pricing measure (the stimulus) and the choice behaviour of decision-makers (the response) are captured in a stimulus-response framework.

The stimulus-response framework is this chapter's main contribution to this thesis, as it summarises the complex interactions between road pricing, behaviour and system performance and provides an easy to read overview for people interested in knowing more about road pricing.

In order to develop this stimulus-response framework we investigate the stimulus of road pricing in Section 2.1 and the responses of different actors are discussed in Section 2.2. In Section 2.3 we then combine both the stimuli and the responses and present the resulting stimulus-response framework.

2.1 Stimuli: Objectives and design dimensions

In this section, we focus on the road pricing policies and measures that serve as stimuli for travellers to behave in a certain way, such that the road authorities can achieve their predefined objectives.

The purpose of this section is to bring order to the diversity of road pricing policies and measures that remain possible when using the definition of road pricing presented in the previous chapter. What policy objectives are supported by road pricing and how different objectives will affect the main characteristics of the road pricing measure are the main issues covered in this chapter. In this chapter, we will therefore discuss the objectives of road pricing and the design dimensions of road pricing measures.

There are many design dimensions with respect to road pricing measures. We distinguish two groups in this section, namely: primary and secondary design dimensions. Primary design dimensions determine what people have to pay and describe how the road pricing measure is differentiated in terms of place, time, user groups and vehicle types. Secondary design dimensions describe how travellers are charged, how they pay, what information they receive, and how enforcement is arranged. Secondary design dimensions do not determine how much people pay, but they do affect how people perceive and can use the system and this will also affect how they react to the road pricing measure.

In Section 2.1.1, we will discuss the policy objectives of road pricing, followed by a discussion of the primary design dimensions of road pricing measures in Section 2.1.2. In Section 2.1.3., we then discuss the secondary design dimensions of road pricing measures. These three elements, objectives, primary, and secondary design dimensions, then come together in Section 2.1.4. Here we will discuss how, in a design process, a road pricing measure takes on a form that meets the policy objectives.

2.1.1 Road pricing objectives

A road pricing policy describes the objective, the intended impacts, organisational and judicial issues, equity issues, etc. A road pricing measure describes exactly who will pay where, when, how and how much. A road pricing policy may therefore be operationalised by one or more road pricing measures. For the design of an effective road pricing system, it is of the utmost importance to be specific and clear about which policy objectives or combination of objectives the road pricing measures are to target. Therefore, before addressing road pricing measures, the most common policy objectives concerning road pricing are first discussed. We distinguish four policy objectives in this section, namely:

- Internalisation of external costs (Marginal cost pricing)
- Solving traffic problems
- Financing infrastructure
- Fairer transport system

Internalisation of external costs (Marginal cost pricing)

All modes of transportation cause some level of pollution, reduction of safety, etc., for users of the transportation system as well as for others. In many cases these external costs of transportation are not fully paid for by the user, or, in economic terms, the external costs are not fully internalised. This leads to inefficient, and sometimes excessive, use of transportation, see Button and Verhoef (1998). Road pricing is considered to be a very effective instrument for welfare maximisation and reducing the societal damage (in monetary terms) of mobility. By applying charges equal to the marginal external costs (the increase in external costs of one extra user) travellers are stimulated to behave efficiently.

In the extreme case that all external costs are included in the road pricing fee correctly, economists speak of a first best road pricing solution. This first best solution would require constantly changing charge levels on each location, for each second and for each road user or

vehicle. First best pricing can therefore never be applied in real life and economists look for second best pricing measures that may achieve comparable effects as the first best pricing solution, but are also practically applicable.

Policymakers are not likely to use the economic definitions of marginal cost pricing in explaining the objectives of a road pricing policy to the public. An example of a road pricing policy where external costs are internalised is the proposed national kilometre charge in the Netherlands, where instead of lump sum taxes, travellers will pay per kilometre driven where the charge per kilometre is differentiated by time, space and vehicle type Ministry of Transport Public Works and Water Management (2007). In this case, the external costs of pollution and delays are included in a charge. The road pricing policy is promoted as being intended to make the transportation system fairer because drivers pay for what they use.

Solving traffic problems

Transportation is often referred to as being a derived demand. This means that transportation is not an objective in itself, but it serves other needs of people and businesses. As congestion increases, time sensitive travellers (and freight movements) can face such deteriorated conditions that they will change the locations of their activities, which can negatively affect the economy of a region. Road pricing can then be an instrument that relieves congestion. The cost of transportation will increase, at least for some people, but the most economically important traffic may benefit. Congestion pricing is used to reduce congestion to optimal or acceptable levels. There are several examples of road pricing policies with an objective of reducing congestion. Singapore Gomez-Ibanez and Small (1994), London Transport for London (1997) and Stockholm Beser Hugosson et al. (2006) are well known examples. In all three cases, a city centre is surrounded by a cordon where car drivers have to pay for either entering or staying within the cordon. In Stockholm and Singapore, the charge is different for different hours of the day. In London, travellers pay a fixed amount for each day their car is noticed within the cordon.

Another approach to improving the accessibility of a region for time sensitive traffic is not to reduce the overall level of congestion, but to improve accessibility for a specific group. Value pricing measures, as implemented in several places in the US, are examples of such an approach. At the I-15 near San Diego Van Amelsfort and Bovy (2000) and at the SR-91 in Orange County, travellers pay to travel on separated, congestion free infrastructure, which in these two cases are HOV lanes, instead of on the still congested main lanes of the motorway. The road pricing fee travellers pay depends on the time people use the facility. The charge is usually higher if there is more congestion on the congested parallel road. The charge mechanism must ensure a congestion free ride using the value pricing facility.

Financing infrastructure or maximising profit

A more traditional objective for road pricing is to finance the construction (and or maintenance) of new transport infrastructure. Toll roads are a widespread and accepted phenomenon in many countries. A toll road may be owned by either a public or a private party. The objectives of these may differ somewhat. Where a public authority may solely be interested in recouping the initial investment, the objective of private companies is more likely to maximise their profit. The latter may lead to less optimal use of road infrastructure from a societal point of view. Examples of government owned toll roads are the Norwegian toll roads around Oslo, Trondheim and Bergen Tretvik (2003). Brisa, Cofiroute, Autostrada, etc. are examples of toll road companies that operate toll roads in different countries in Europe.

Fair pricing structure for road use

The introduction of a road pricing measure may alternatively have the objective of restructuring the current pricing structure of the transportation system in such a manner that the price people face depends on their usage of the system. This fair use policy does not change the annual cost of travel for the average traveller. Those who travel more than average will pay more and those who travel less will be better off. Although the cost for the average traveller does not change, it should not be assumed that no behavioural responses are to be expected. If they want to, people can now save money by adjusting their travel behaviour.

Fairness is the main policy objective being communicated to the public for the proposed kilometre charge in the Netherlands. Although the kilometre charge is promoted as a fairer system, the differentiation by time, space and vehicle type shows clear resemblance to a marginal cost pricing system. We therefore discuss it there as well. Replacing the taxes on car ownership and car purchase with a kilometre charge is thought to be fairer since only the people that use the road, pay for the road (Ministry of Transport Public Works and Water Management (2007)). All revenues should also go to the construction and maintenance of infrastructure.

2.1.2 Primary design dimensions of road pricing measures

One road pricing measure may be effective for one policy objective, while being ineffective or even counter-productive for another objective. When seeking to maximize profit, for example, the charge should not be too high or many travellers may avoid the road and thus not pay, while for decreasing congestion a high charge may be very effective. This section discusses the range of design dimensions for road pricing measures. In Section 2.1.4, the policy objectives and design dimensions are combined to provide insight into the relationship between policy objectives and the design of road pricing measures.

A pricing measure has to be ‘designed’ and can be characterised by different ‘design’ variables. Given the objective, assumptions and boundaries of the road pricing measure, an optimal design can be made. The design variables that determine the optimal road pricing design include the classic questions: what (to levy), when (to levy how much), where to levy, who to charge, how to charge? These questions relate mainly to the different levels of differentiation of the road pricing measure, which will each be discussed in more detail in the subsequent sections. In this research, we do not attempt to optimise road pricing measures given a policy objective, this type of research has, for example, been conducted by Joksimovic (2007), Sumalee (2004), Brands et al. (2008). Our objective is to better determine the effects of a given road pricing measure on the traffic system. In general, the differentiation of road pricing fees will make it possible to charge the right amount to different travellers, travelling in different places and at different times. A well designed differentiation will always make the road pricing fee more effective. Well designed, however, is hard to define and entails some secondary design dimensions as well.

Differentiation by location

A road pricing measure may levy different charges on different roads, road types or in different areas. The purpose of differentiating charges by location is to improve the distribution of traffic over different areas or roads. Roads that, as a policy objective, should have less traffic will receive a higher charge than roads where higher traffic volumes are less problematic.

Examples of the differentiation by location of road pricing measures are, for one, toll roads where the toll is generally only levied on sections of road which need to be financed from the revenue, for construction and maintenance. There are several good examples of a cordon charge around a city centre (London Transport for London (2008), Stockholm Beser Hugosson et al. (2006), Singapore Gomez-Ibanez and Small (1994), and Oslo Tretvik (2003)), where travellers pay for either entering the cordon or crossing any cordon border. The objective here is to improve conditions in the city centre by reducing the number of vehicles. A side effect of cordon charging may be that traffic is diverted around the cordon, deteriorating traffic conditions there as a consequence. A last example is the freight kilometre charge in Germany, which is only levied on the motorways. The objective here was to create a fairer system of road taxes for German transporters compared to foreign transit freight traffic (which concentrates on the motorways). It seems that most road pricing measures use some type of differentiation in place, although the method depends clearly on the objective of the road pricing measure. We distinguish the following levels of differentiation with respect to place, namely by:

- Road segment
- Route
- Road type
- Area
- Network

Differentiation by time

When road pricing measures are differentiated by time, the charge is not constant over time. Given the different policy objectives, there may be different reasons why differentiating the road pricing fee in time is important. When, for example, the objective is to internalise the external costs, time differentiation may be applied in order to include the fact that external costs are not constant over time. In the case of the objective being to solve traffic problems, it makes sense to charge higher fees during the times at which the traffic problems occur.

Differentiation by time can be looked at from different levels. A road pricing fee will most likely not have a permanent status, but will be changed over time as a result of inflation, etc. This is not what we define as differentiation in time, since it is less a design dimension than a consequence of changing exogenous conditions. A road pricing fee can, however, also be designed to change with seasons, months, weeks, or day of the week. This between-day differentiation in road pricing fees is, for example, used on the SR-91 Express Lanes (2008). Besides between-day differentiation, there also exists within-day differentiation of road pricing fees, where a fee may differ between morning and afternoon, etc. In this thesis, we consider three levels of within-day differentiation by time, namely:

- Dynamic differentiation
- Variable differentiation
- Fixed charge levels

With dynamic road pricing, the charge may change instantly as a result of changes in traffic conditions. An example of dynamic pricing is the I-15 Value Pricing project in San Diego, where tolls are updated every 6 minutes (see Van Amelsfort and Bovy (2000)). With variable pricing, the fee changes within a day, over different days of week, month, and or season according to a published fee schedule. Examples of variable road pricing measures are the SR-91 Hot lanes (2008), the Stockholm congestion charging trial Beser Hugosson et al. (2006) and the London Congestion Charge Transport for London (2008). These three

examples do, however, have different levels of differentiation with respect to time. In the simplest form, the road pricing fees are not differentiated over time. This may be used for toll road projects aiming at raising revenues to recoup infrastructure investment and maintenance costs.

When we discuss the time differentiation of a road pricing measure in this thesis, we mean a within-day differentiation. Furthermore, we introduced time-varying road pricing measures in the title of this thesis and with time-varying we mean road pricing measures with either a dynamic or variable differentiation.

Differentiation by user groups

Not all road users behave in the same manner or respond equally to road pricing. In order to increase the effectiveness of a road pricing measure, it is therefore beneficial to adjust the fees according to the characteristics of the travellers and their trips. In order to keep the system practically feasible, instead of individuals, different groups of users may be identified. Besides effectiveness of the road pricing measure, acceptability is another important reason for differentiation between user groups. Within cordon pricing measures, the inhabitants living in the cordon may, for example, be exempted from paying a road pricing fee. Also, elderly people or disabled travellers may be compensated. As a policy objective, differentiations in user groups can be appealing, but they may not always be practically applicable since it may be impossible to determine to which group a car (or its driver) belongs.

Examples of differentiation by different user groups are the discount (90%) for residents within the cordon in the London congestion charging scheme and the exemption of the people living North-East of Stockholm (Lidingö) in the congestion charging trials. In both cases (London and Stockholm), disabled drivers are fully exempted from the congestion charge.

Within this thesis, we will consider charges that are differentiated between user groups. In Chapter 10, we will evaluate different rewards schemes, where travellers can earn money for not travelling at peak hours. Only participants are able to receive this reward.

Differentiation by vehicle type

The differentiation of road pricing fees according to vehicles types is a very common form of charge differentiation. Depending on the policy objective, the use of a road by a certain vehicle may be desirable or not. If a vehicle type is not desirable, or less desirable than competing types, the charge should be higher. With toll roads, for example, trucks are often charged more than passenger cars because they cause more damage to the road surface. In the London congestion charging measure, cars driving on LPG are exempted since they are believed to cause less pollution. In the proposed kilometre charge for the Netherlands Ministry of Transport Public Works and Water Management (2007), the charge will also be differentiated by vehicle types, depending on their environmental characteristics. In Germany, Switzerland and Austria, road pricing measures specifically for trucks (HGV's) are implemented.

In this thesis, we do not consider the differentiation by vehicle types, although the modelling framework we develop in part C allows for such differentiation. It was used, however, in the modelling work we produced for Tillema (2007), who evaluated different kilometre charging schemes for the region of Eindhoven.

2.1.3 Secondary design dimensions of road pricing

Secondary design dimensions describe how travellers are charged, how they pay, what information they receive, and how enforcement is arranged. The HOW aspect of road pricing is important and affects the cost-benefit ratio of a road pricing measure as well as the behavioural responses and acceptability of the measure. In the group of secondary design dimensions, we consider five dimensions: 1) Information provision, 2) Identification systems, 3) Charging systems, 4) Payment systems, and 5) Enforcement systems. These five dimensions are shown in Figure 2.1. On top is an information provision layer, in which the designs of lower level systems (and the primary design dimensions) are well explained to travellers in order to provide an understanding of the road pricing measures as a whole. On the lower level, we then include the four remaining design dimensions in the chronological order in which they will be used. First, a vehicle or person needs to be identified, and then a charge can be calculated based on location, time, user group, and vehicle type. When the charge is known, the traveller has to pay that charge. This payment may occur at that moment or at a designated later time. When a traveller does not pay the charge, however, some enforcement needs to be in place to force the traveller to pay.

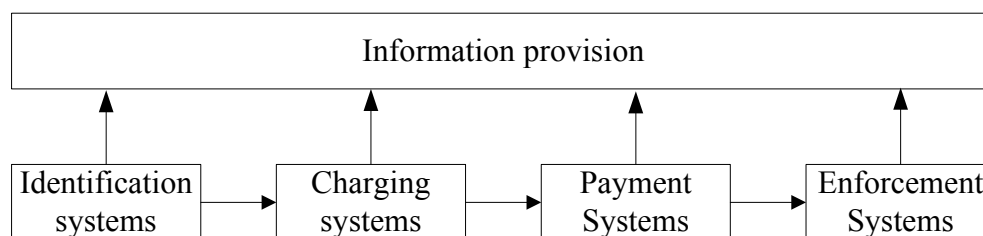


Figure 2.1: Secondary design dimensions

For each of these design dimensions, there are different designs possible, where choices for a specific design for one dimension affects the possible designs in other dimensions. If, for example, the choice is to use GNSS technology as a charging system in a kilometre charge scheme, toll booths are not a suitable payment system and a barrier is not a suitable part of an enforcement system. We will now briefly discuss each of the five secondary design dimensions.

Information provision

Information provision to travellers is of key importance to the effectiveness and acceptability (for research about acceptability see Ubbels (2006) and Schuitema and Steg (2008)) of the system. People cannot make ‘good’ travel decisions if they do not know how much they will have to pay, where they must pay, and at what times. Besides information on how the system works and about how travellers have used the system, information is also needed about why the system is implemented, how, for example, revenues are used, and what the effects of the road pricing measure are or will be.

Identification systems

In many of the road pricing measures that are now designed or that are recently implemented, travellers do not need to stop to pay the charge because they are charged automatically. In those cases, the identification of who needs to be charged becomes more complex than at the traditional toll booth. There are three main types of identification technologies Curacao (2008), namely: 1) automated license plate recognition (ANPR), 2) dedicated short range communication (DSRC using infrared, radio, etc), and 3) mobile communication devices (such as GPRS, EDGE, HDSOA, etc).

With Automatic Number Plate Recognition (ANPR), images of the license plates of vehicles are recorded using cameras. These images are then interpreted using ANPR computer software, and finally the interpreted vehicle license is compared to a database of registered users. The owners of those vehicles can then be charged. The London congestion charge scheme uses hundreds of cameras, both stationary and mobile units, and ANPR to help monitor vehicles in the charging zone. The advantages are that enforcement operations have no impact on traffic flow, and the system provides photographic evidence to support enforcement proceedings. The downside of ANPR systems is that they are less easily scalable to larger regions or more check points. Also, this system is space saving in comparison with entry points / toll collection areas. However, ANPR requires that street furniture be installed, which can cause problems in historic urban centres.

Dedicated Short Range Communication (DSRC), based on an on-board unit (OBU), is now a common technology used throughout the world by toll road operators. Passive tags (no internal power supply) are activated by a roadside transmitter, which sends a signal to the tag that responds with its identity. This response is read by an associated receiver at the roadside, enabling a charge to be added to or deducted from a centrally held credit or debit account. Active tags with their own source of power can hold funds on inserted smart cards. Tags can be used with a variety of charging schemes, including entry and area licensing, cordons, cells and screen lines. Tags make identification easier than with ANPR but require more street furniture, and require vehicles to be fitted with the equipment.

Mobile communication devices can be used for identification when they connect to the back office or when a connection is requested by the back office. Besides transmitting the identification details, the mobile device can also transmit other data about, for example, the travel behaviour or the charges that need to be paid. The benefits of mobile communication devices is that they do not require additional road side equipment apart from the network masts that are often already in place. Additionally, they increase the system's flexibility in terms of when identification occurs (in time and place). The downside with mobile communication is that both the device and the data transmission costs are likely more expensive than for other identification technologies.

Charging systems

Charging systems create a link between an individual traveller and a certain location and time. Using the road pricing fee schedule, the system then determines the charge that has to be paid. In some cases, this charge is directly paid, but in other cases the individual charges may be summed. There even exist post/trip charging systems that only record where and when the vehicle is driven, and at some point in time these data are used to calculate the price the traveller is charged, at the end of the day or month, for example. We consider three main options for charging: (1) manual charging, (2) in-vehicle charging, and (3) charging in the back office.

Manual toll collection / Automatic coin collection machines

The operation of point-based road pricing schemes is still mostly based on manual toll collection or automatic coin collection machines at toll booths. The toll collection booth is, in essence, a combined charging and payment system. An advantage is that it offered a high level of reliability and enforcement. It is a simple, effective and well accepted technology, but costly. Moreover, since vehicles have to stop, serious congestion is often created around the toll collection areas, which are space consuming as well. Also, this system is less appropriate for (variable) congestion charging and for large urban areas where roads have many exits.

In-vehicle charging

With automatic in-vehicle charging, the amount that needs to be paid is computed in the car. This means that some on-board processing unit needs to be installed in which the road pricing tariffs are stored. One of the benefits of in-vehicle charging is that the privacy of travellers is better assured, since only the charges need to be shared with the collecting authority, not the time and place of the travel (Dutch Data Protection Authority (2001)). In-vehicle charging does, therefore, require some computing power in the vehicle, which costs money to install and maintain. Other downsides of the system may be that if tariffs change, these changes need to be correctly programmed into the OBUs. In-vehicle charging may also be more sensitive to fraud.

On-board units that use in-vehicle charging are often referred to as thick-clients, as the units (clients) can do more than just identification. With, for example, a kilometre charge scheme, the complete road map may need to be installed on the OBU in order to determine where a vehicle is and what charge applies there. To determine the location of the vehicle on the map, GNSS technology is used. Having an updated road map in an on-board unit may then allow for route navigation services for the drivers, which could be considered by them to be a benefit. Such type of so called value-added-services (VAS) may result in higher acceptability and improved cost-benefit ratios (Ministry of Transport Public Works and Water Management (2008)).

Back office charging

With automatic back office charging, the specific form of operation depends on the price differentiation by location. For a localised road pricing scheme, where travellers are identified when passing certain points in the network, a signal with the price can be sent to either the vehicle or directly to the back office. When a network wide road pricing scheme is operated, such as a kilometre charge, the data of where a traveller drove at what time is sent to the back office, where the price of a trip, or even multiple trips, is computed. The benefit of back office charging is that changes in the charge levels can more easily be implemented than with in-vehicle charging. The system is also less sensitive to fraud, since all kinds of data checking can be conducted in the back office. Since less computation power is needed in the vehicle, the system is also likely to be cheaper. A possible downside of back office charging is that the collecting authority may have access to sensitive private data on the travel behaviour of customers. On-board units that use back office charging are often referred to as thin-clients, as these units only log and transmit identification, location and timestamp data (Ministry of Transport Public Works and Water Management (2008)).

Payment systems

When a traveller is identified and the charge is determined, the traveller needs to pay. This need not be done directly, and the payment systems determine how and when travellers can pay the determined charge. We consider two types of payment systems, namely manual systems and automatic systems. With manual payment systems, the traveller has to perform a payment task his or herself. This may involve a range of payment techniques from sending an SMS message to the back office or by transferring funds to the bank account of the collection authority.

With automated payment systems, the travellers have to approve automated payment once, and after that the road pricing fees are automatically deducted from an account. A credit card payment is then only considered an automated payment if the traveller is not required to manually pay the resulting credit card bill. The main advantage of automated payment

systems is that transaction costs for the collection authority are reduced, while at the same time, it is simple to use for travellers and reduces the risk of their forgetting to make a payment. The main disadvantage of automated payments is that travellers are less informed about how much they pay, and as a consequence have different behavioural responses towards road pricing.

A number of options and payment channels exist for the transfer of funds between the user of electronic charging and the scheme operator (Curacao (2008)). For instance, the London congestion charge can be paid online, by SMS, by phone, at a shop, at a self-service machine or by post. In general, the transaction process is easier and faster for registered users, and some options like SMS and phone require the user to register. Advantages for registered users are that they can view their payment history online, and they can benefit from automated identification and payments systems. In some cases registered users pay less, but even with identical charges, travelling can be more convenient as a registered user.

In Stockholm, more than 70% of the congestion tax is paid by direct debit, followed by payment at kiosks and retail outlets as the second most common payment method. Internet payments using charge cards, or bank giro, constitute only a small fraction of the total payments. In Norway, the AutoPASS co-ordinated tag and beacon based payment system has been in operation since 2004, now involving more than 25 project sites of which 6 are urban toll ring systems. Regardless of where passage is made, the passage will be registered and charged to the account at the toll operator where the driver has a contract. This contract can be based on either pre or post payment of charges. Those without a valid tag can post pay at a nearby petrol station, or they receive an invoice by post.

Enforcement systems

The systems for identification, charging and payments are probably not 100% accurate and it is not unlikely that travellers try to tamper with these systems or refuse to pay. For all these instances, some enforcement systems need to be implemented. Some of this can be legislative in nature, but some technologies might also be used to detect abuse and malfunction. The ANPR systems used for identification can, for example, also be used as a system for enforcement. In the case of a kilometre charge, periodic odometer checks may be used. De Jong (2001) discusses how to design a kilometre charge scheme that is insensitive to fraud and protects the privacy of travellers. Concerning enforcement, he distinguishes between logical and physical systems that reduce the possibilities for fraud. Logical systems relate to legislation, procedures, and organisational issues, while physical systems focus on reducing the opportunities travellers have to tamper with technical devices. He furthermore argues that physical system should need a minimum of physical enforcement systems and the focus should be on appropriate logical systems where the responsibility to provide correct data to the collecting authority lies with the traveller, not with technology provided by an authority.

2.1.4 Design process: matching policy objectives and design dimensions

In the previous sections, we have discussed road pricing policies, design dimensions of road pricing measures, and technology options for charging and payment. Translating a policy objective into a fully specified road pricing measure requires many decisions. Figure 2.2 presents different levels of policy-making that might be identified in the decision making process. On the highest level and with the smallest detail, policy objectives and intended impacts are formulated. This level is called the road pricing policy level, sometimes also called road pricing strategy. On the next level, called the road pricing scheme level, the objectives are translated into a scheme that considers the necessary differentiation of charges,

for example in time and space. The level of differentiation has a direct impact on the requirements of the charging and payment technology, which are also included in this level. Based on the chosen levels of differentiation, the exact spatial and temporal patterns of this differentiation have to be determined, which is done at the road pricing pattern level. Finally, the exact levels of the charges (the amount) have to be chosen. The road pricing measure is the lowest level with the highest detail, where all tolls have been determined and support the choices made on higher levels.

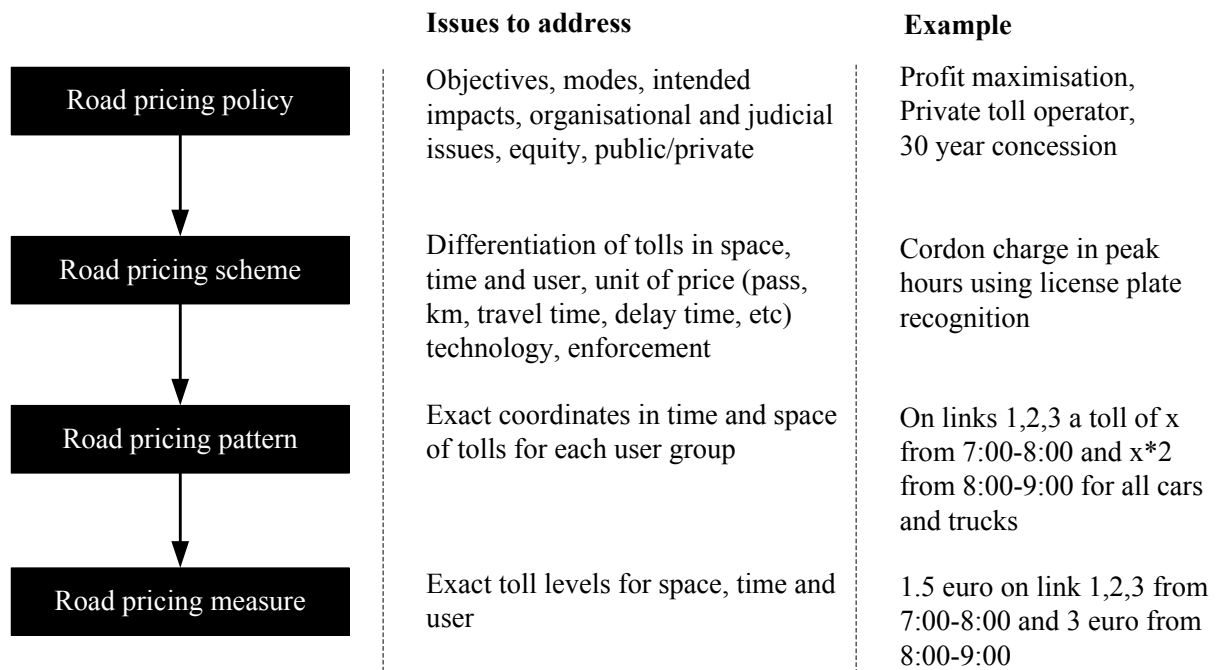


Figure 2.2: levels of policy-making for road pricing implementation

The reality of decision making may not follow the decision steps presented in Figure 2.2, since these processes are often driven by political aspirations and possibilities. There may, for example, be consensus on the road pricing measure, while different political entities support the measure from different perspectives or objectives. For one policy objective there is probably not one unique road pricing measure and similarly one road pricing measure may support more than one policy objective (be it sometimes less effective and or efficient).

As may have been apparent from the examples of road pricing measures given in the previous sections, the different objectives of the road pricing policies lead to different designs of road pricing measures. For solving traffic problems in cities, a cordon charge seems a successful scheme; for marginal cost pricing, a differentiated kilometre charge scheme seems appropriate. In Table 2.1, we combine the various policy objectives, design dimensions and technologies and have assigned ticks (✓) for each of the suitable level of design dimensions and technology for each policy objective. As the table shows, not all cells are ticked, indicating that some combinations are not or are far less appropriate. We will highlight a few important aspects.

Table 2.1: Relationship between objectives and design dimensions

Policy objective → Design dimensions ↓			Internalisation of external costs	Solving traffic problems	Financing infrastructure	Fairer transport system
Primary design dimensions	differentiation by place	road segment		√	√	
		cordon		√	√	
		network	√	√	√	√
	differentiation by time	Fixed			√	
		variable	√	√	√	√
		dynamic	√	√		
	differentiation between user groups	none			√	
		exemptions	√	√		√
		location	√	√		√
	differentiation by vehicle types	freight/cars			√	
		environment	√			√
Secondary design dimensions	Information provision	system	√	√	√	√
		promotion	√	√	√	√
	Identification systems	manual			√	
		DSRC		√	√	√
		mobile	√	√	√	√
	charging systems	manual			√	
		in-vehicle	√	√	√	√
		back office	√	√	√	√
	Payment systems	manual	√	√	√	√
		automatic		√	√	√
	Enforcement systems	physical	√	√	√	√
		logical	√	√	√	√

Charging by road segment only seems appropriate for infrastructure financing (toll road) projects. For the other objectives, the scope of a road segment is too small and the benefits generated on the road segment may be easily offset by negative effects in the network elsewhere.

For solving traffic problems, all differentiations in place may be appropriate, depending on the type of traffic problems. It is unlikely that traffic problems occur during the entire day, however, and as peak hours can be identified, it is less appropriate to use a constant, fixed charge throughout the day. A constant charge may lower demand and thus alleviate traffic problems, but it does not directly motivate travellers to avoid the peak hours.

With respect to differentiation between user groups, it seems appropriate to always address the needs and possibilities of different individuals, so that every individual receives the right monetary incentive for 'optimal' behaviour. In the case of financing infrastructure, the underlying motive is not that of changing the behaviour of travellers, so in such a case it is important to make users 'feel' the charge as little as possible.

Finally, the technology aspects of road pricing are increasingly moving towards automated charging and payment methods. The latter may not be completely desirable, since an

automated payment may influence the sensitivity of the user towards the road pricing charge. For anything other than financing infrastructure, it is not appropriate to stop traffic and have travellers pay directly at toll booths.

2.1.5 Summary and conclusions

In this section, we have looked at the objectives, design dimensions and technologies of road pricing. Clearly the objective determines, although not uniquely, the design of the road pricing measures. Looking at the design dimensions of road pricing measures, we find that not all levels are appropriate for a specific policy objective. We have identified design dimensions for road pricing measures, and have defined primary and secondary design dimensions. Primary design dimensions determine the level of road pricing fees and how fees are differentiated by time, place, user groups, and vehicle types. Secondary design dimensions determine how the system works and include information provision, identification systems, charging systems, payment systems and enforcement systems.

In the discussion on the appropriate levels for the different design dimensions, we found that the level of differentiation relates to the direction of intended road user behavioural responses. The behavioural responses of road users towards road pricing are thus important to understand when designing a road pricing measure. The question of what the objective of road pricing should be may then, to some extent, be replaced by the question of how a policy maker wants road users to behave. The road pricing measure should be designed in such a way that road users are motivated to show this behaviour. Again, an understanding of these behavioural responses of road users is therefore of key importance for designing ‘good’ road pricing measures. A large part of this thesis, starting with the next chapter, will be devoted to researching the potential behavioural responses of road users to road pricing measures.

In this thesis, we will focus on how the differences in primary design dimensions affect choice behaviour and network effects. We are particularly interested in time differentiated road pricing measures, hence the time-varying descriptor in the title of this thesis. With regard to the secondary design dimensions, we assume that all travellers are completely informed about the road pricing measure and that they take the road pricing price into account during their decision making processes.

2.2 Responses: behaviour of actors and the aggregate system

In the previous section, the stimulus side or the road authority side was presented, in which policy objectives need to be translated into concrete road pricing measures. What are the design dimensions of the stimulus that correspond with the policy objectives? The resulting road pricing measures directly affect the actions and wellbeing of road users, but may indirectly affect other actors as well. This section aims to give an overview of the different actors that are potentially affected in their actions and wellbeing by the road pricing measure, and describes their possible responses to the road pricing stimuli.

The main contribution of this section is to provide an overview of behavioural responses of actors involved, not only the road users, including direct and indirect effects as well as short and long term effects. These behavioural responses will be presented in a conceptual framework in order to provide a structured overview. All individual behavioural responses when aggregated affect the transportation system, as will be indicated.

As it is impossible to include all actors and behavioural responses into the analyses and modelling exercises that follow in the succeeding parts of this thesis, we will choose the most important responses based on the analyses in this Chapter.

This section is structured as follows. First, the different actors involved will be briefly introduced in Section 2.2.1. The (direct and indirect) responses of each actor are then discussed in more detail in Section 2.2.2. We look at what decisions actors may change and how when road pricing is introduced or changed. The result on the transportation system is discussed in Section 2.2.3. Finally, a summary and some conclusions are provided in Section 2.3.

2.2.1 Actors affected by road pricing

Many people and organisations may be affected by road pricing, directly or indirectly. Clearly, road users are directly influenced because they will have to pay the road pricing charges. Travellers who are not using the road, however, may also be affected. Train users, for example, may experience more crowded trains as some road users shift from car to public transport. Relevant actors being affected by a road pricing measure are:

- Households
- Road travellers
- Other travellers
- (Non-travellers)
- Companies/employers
- Other actors

Figure 2.3 shows that these actors interact directly with each other but also indirectly through transport system changes that may be caused by other actors. We briefly discuss each of the actors and then discuss their behavioural responses.

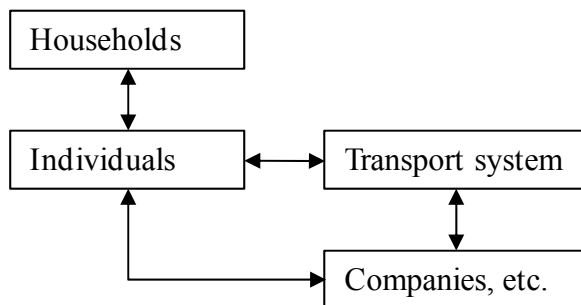


Figure 2.3: Interactions between actors and the transport system

Households

Households consist of one or more individuals who engage in different activities during the day. Since not all activities can be done at one location, these individuals need to travel. Individuals/companies who travel by car before introduction of the road pricing are faced with an increase in monetary cost for travel. These are the actors that are directly affected by the road pricing measure; all other actors are affected indirectly by road pricing. By indirectly affected, we mean that these actors experience changes in their lives as a result of changes in the behaviour of road users. Members of the household that do not travel by car may be affected because of changes in behaviour of the road travellers, changes in the transportation system and changes in the household budget. In the overview of actors which we presented above, we therefore also included non-travellers as a group of actors.

Companies/Employers

Apart from private individuals, companies also generate traffic. The simplest example is probably a trucking company or postal service. These companies are directly affected by the road pricing measure as well. Companies and employers are indirectly affected by road pricing measures because clients or employees have to pay the road pricing charges and because of changes in traffic conditions. Employers may need to provide some compensation to clients and/or employees. Note that one positive indirect effect of road pricing may be very important for businesses: as traffic conditions improve and travel times decrease and become more reliable, the costs for businesses also decrease. This is one of the most important intended, although indirect, effects of road pricing policies.

Other actors

Other actors, such as local governments, stakeholder groups, foreigners, etc. may be affected as well, either directly or indirectly. Local governments may, for example, be responsible for traffic and transport planning in their community. As a result of road pricing somewhere else, they might need to invest differently in road and public transport infrastructure. Media with different political backgrounds may also respond to the introduction of road pricing with attempts to steer the public, and as a result, the politicians, towards their desired alternative.

2.2.2 Behavioural responses of actors to road pricing measures

When looking at the behavioural responses of actors, we are interested in determining the changes in behaviour in a new stable situation that will slowly settle in after introduction of the road pricing measure. We therefore do not consider how travellers will respond on the first day, nor do we look at the transition from that first day to a stable situation. In this section, the behavioural responses of individuals, companies and other actors are discussed.

Individuals

When road pricing is introduced, it is expected that each directly affected individual will try to avoid paying, as far as constraints at home or at the destination allow. This may also result in no change in behaviour from the road user, who is thus simply accepting payment of the road pricing charges. The road users in a household are directly affected by the road pricing measure and as a result may show the following behavioural responses:

- Change nothing in travel or mobility behaviour – rearrange budget
- Change route
- Change departure time
- Change mode (for example bicycle, public transport, carpool, etc)
- Change / combine activities
- Change trip frequency
- Change destination
- Change mobility (car ownership, public transport passes)
- Change residential location
- Change job

The behavioural responses are likely to occur in some hierarchy. Easier changes are made first, and if these are not sufficient, change occurs in more difficult aspects of choice behaviour. How this hierarchy is structured depends on the road user and the purpose of travel. It may be easy to choose another store when shopping, thus avoiding the payment of charges. It is harder to change to public transport when buying a widescreen TV. On the other

hand, choosing a different place to work may be more difficult than using public transport to go to work. In Figure 2.4, we present a structure of behavioural responses. The responses are categorised into three groups: 1) trip level responses, 2) mobility level responses and 3) location level responses. We also distinguish between, short, medium and long term behavioural responses. As can be seen in Figure 2.4, we expect that trip level responses occur faster than location level responses. More than the other levels of responses, the trip level responses can be decided by the individual within the household, while other responses are often household decisions. This also affects the response time of households towards road pricing.

Companies and employers

Companies that are directly affected have to pay the road pricing charges. If companies do not change their behaviour, this results in an increase in costs (neglecting positive indirect effects) and lower profit margins. As a response, companies may:

- increase the price of their products or services
- change/resize their product
- develop transport reduction strategies, such as:
- use different logistic concepts
- use different size vehicles/trucks
- relocate to cheaper areas
- open more offices closer to clients

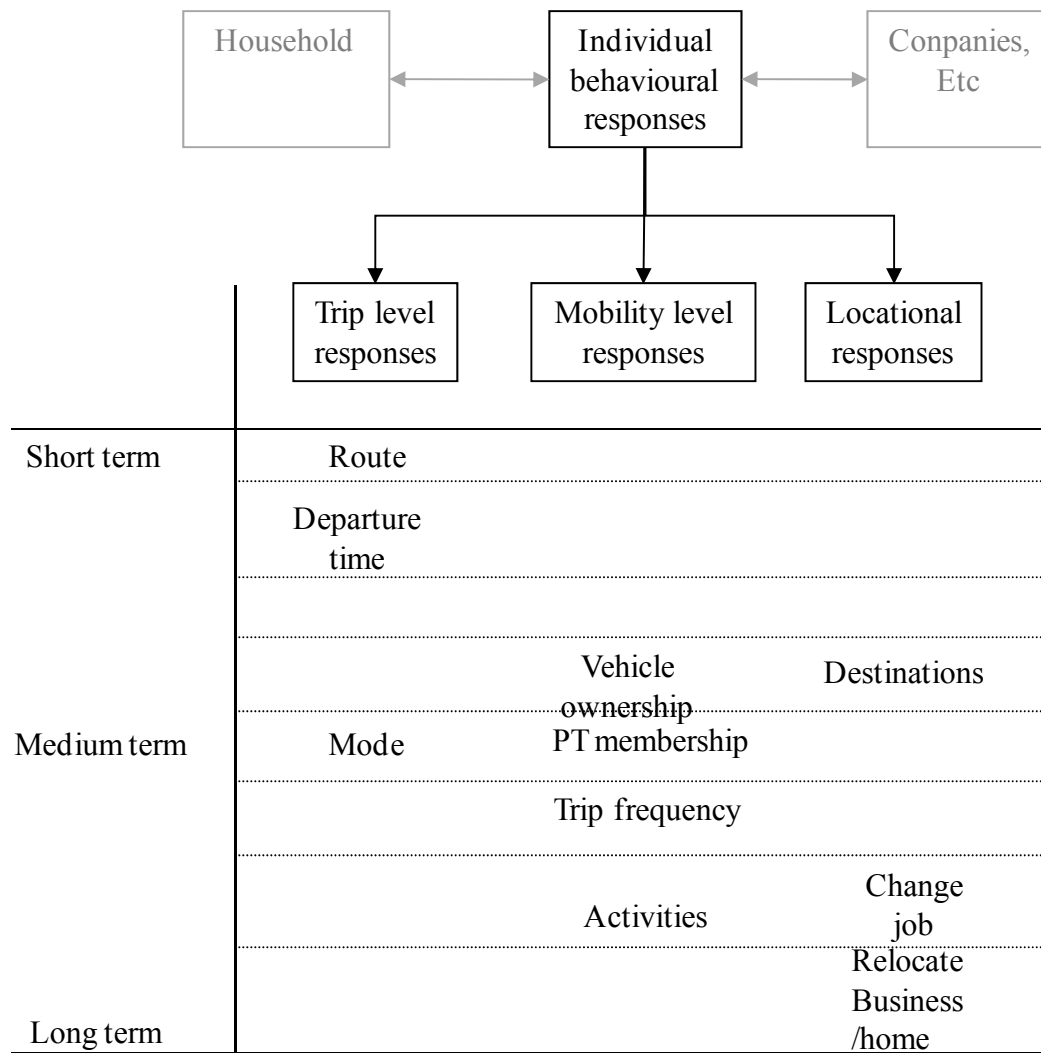


Figure 2.4: Structure of behavioural responses to road pricing

Indirectly affected companies or employers may respond to the road pricing measure by:

- compensating clients for increased travel costs
- changing work conditions/contracts with employees
- compensating employees for increased travel costs
- changing working hours
- supporting teleworking
- supporting car/vanpooling
- developing strategies to benefit from improved accessibility
- using different logistic concepts
- using different size vehicles/trucks
- relocating to areas with relieved congestion

The objective of companies is likely to have a healthy profit margin in the longer term. As a direct effect of road pricing, their costs may increase. The net effect of road pricing on a company, however, is determined also by the indirect effects, and these may well be positive. In terms of affected companies, there may be disproportionally affected sectors (positive and negative) as a result of road pricing. The automobile industry, freight related companies, public transport operators, etc. may be affected differently than internet companies, banks, etc.

Other actors

The category ‘other’ actors is diverse and, as a result, may cover a wide range of behavioural responses. Here, we briefly consider the behavioural responses of other government bodies. Different government bodies (for example local government in a national road pricing measure) may be directly affected if, for example, government vehicles pay road pricing charges as well. They may be indirectly affected if traffic patterns change to an extent that requires additional traffic measures from local governments, for example, different traffic light settings, changing maintenance intervals, changing demand for parking, changes in demand for public transport and bicycle infrastructure, etc.

2.2.3 Aggregate effects of individual behavioural responses

The net effect of the individual responses is what is of importance to the policy makers. The road pricing objectives are defined on an aggregate level. In this section, we show what aggregated effects may be expected. Again, we distinguish between short, medium and long term aggregated effects. These aggregate effects can be measured in terms of flows, travel times, etc, and we categorize these effects into four main categories, namely: 1) road level changes, 2) Origin-Destination (OD) level changes, 3) mobility level changes and 4) location level changes.

By road level changes, we mean that demand for travel does not change, but that this demand is distributed differently in time and over different routes. In the OD-level, demand changes as a result of changes in mode, destination and frequency of travel. Here the aggregated effects of behavioural changes are included when the choice environment remains the same. On the mobility level, the aggregated effects are included when different mobility options have been acquired by travellers. On the last level, the road pricing measure has led to the different spatial development within regions, cities, etc. Urban sprawl may, for example, reduce as a result road pricing. All these effects are shown in Figure 2.5.

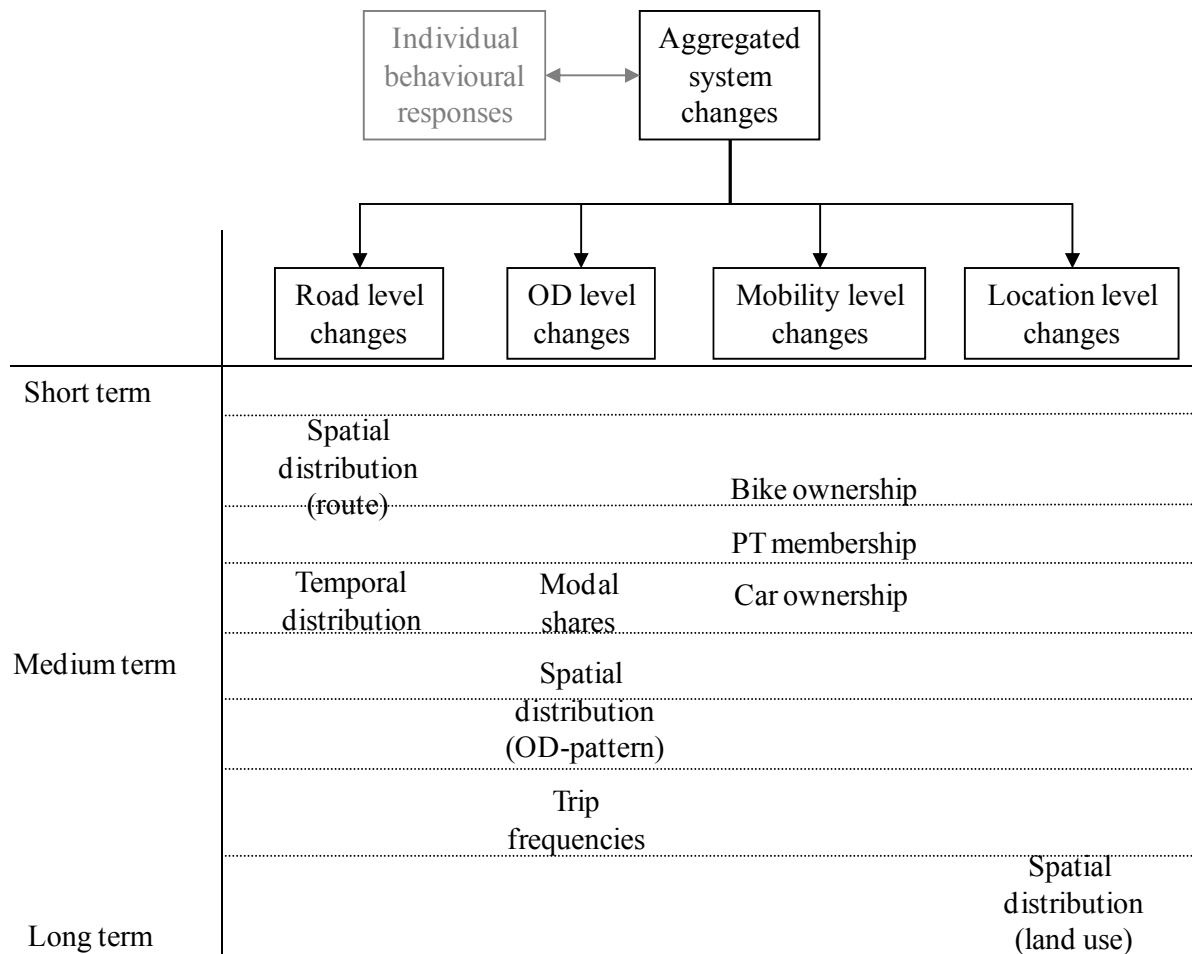


Figure 2.5: Aggregated effects of road pricing on the traffic system

As shown in Figure 2.5, it will take time (years) for all the aggregate effects to manifest. Meanwhile, the system will change as a result of other changes, either autonomous, such as population growth, or as a result of further changes to the transport system. The effects of changes in land use potentially have a large impact on the traffic system and can then not be neglected in the assessment of road pricing measures.

2.2.4 Summary and conclusions

In this section, the behavioural responses of individuals to road pricing have been described. We distinguish between the directly and indirectly affected individuals who may adjust their behaviour. The behavioural responses may be short term, immediate reactions to the road pricing measures or medium and long term reactions, and we distinguished between trip, mobility and location level responses among travellers. The individual responses may result in aggregated system effects, which were also discussed in this section. We categorised the aggregated effects into four groups and separated them into short, medium and long term effects. In order to assess the effects of road pricing measures, it is clear that a multitude of different behavioural responses need to be investigated in order to determine their aggregated system effects.

All of the different actors' behavioural responses will not occur directly following the introduction of a road pricing measure. It may take years, especially for locational changes, before changes in land use patterns become apparent on an aggregate level. By then, it may even be hard to attribute those changes to the introduction of road pricing. The contribution of

these longer term changes to the policy objective may, however, be significant. We therefore conclude that it is important to forecast both the short term effects of road pricing and the long term effects. In this thesis, we will concentrate on forecasting the long term effects of road pricing, under which changes may take place which result in a new stable traffic system.

2.3 The stimulus-response framework

In Section 2.1, we presented the road pricing policies and the design dimensions of road pricing measures, and we discussed the interactions between the two. In Section 2.2, we then discussed the actors, their potential behavioural responses and the aggregate network effects resulting from road pricing. In this section, we combine all these elements, the road pricing measure, the behavioural responses and system changes, into a comprehensive stimulus-response framework.

Figure 2.6 shows this stimulus-response framework. On the left side in the framework, the road pricing measure is depicted as the overall stimulus with its different components. The different components that together form the road pricing stimuli are taken from Section 2.1. Depending on the characteristics of the traveller and his/her individual decision making process, the individual behavioural changes result. The behavioural responses are taken from Section 2.2.2.

The behavioural changes affect the system on different levels, the transport system effects of which were discussed in more detail in Section 2.2.3. The stimulus-response framework also includes effects on the economy and social structure. The effects on the economy and social system have not previously been discussed, as they are not a topic of research in this thesis, but they are important to mention in a stimulus-response framework.

Besides the road pricing stimuli, there may be other stimuli that are introduced together with road pricing which can affect the behavioural responses as well. Although we recognise that there may exist other stimuli that affect the decision making of travellers, we will not discuss them in detail here. Instead, we included different groups of potential stimuli on an aggregate level, namely: transport, economic, political, social/personal, and technological stimuli.

In Section 2.2.2, we also discussed behavioural changes of other actors. These actors and their responses are included in the framework below the box on individual traveller decision making and responses. Given the behavioural responses of both the travellers and other actors, and the system changes that result from that, two feedback loops are included in the framework. The first feedback is between system effects and responses of actors. This interaction has been discussed in different locations in Chapter 1 and Chapter 2. The second feedback loop has not been previously discussed and consists of an interaction between system effects and road pricing stimuli. The effects of road pricing may be somewhat different than expected as a result of other stimuli, other road user behavioural responses and other actors.

In order to further explain the stimulus-response framework, we briefly discuss an example road pricing measure using the framework. Assume that a time differentiated road pricing measure has been implemented. During the morning and afternoon peak, higher charges are levied. As a result, a portion of the travellers decide to travel outside peak hours, some start carpooling or changing their mode of travel, and some pay and do not change their behaviour. This results in improved travel conditions during the peak hours. Some travellers and other

actors may use these improved conditions to travel during the peak hours again. This will lead to deteriorated conditions again, and the first feedback loop is entered until stable conditions occur. In order to support the road pricing policy, some employers may make working hours more flexible and implement ICT measures to support working from home. As a result of these supporting measures, the traffic conditions further improve and the first feedback loop is entered again. Also, as a result of all these changes, some of the travellers that are now using public transport sell their cars, and car ownership goes down. Car sellers may respond by lowering car prices, which increases the demand for cars again. At the same time, the increase in demand for public transportation leads to price increases for tickets, since this is more beneficial for operators than adding capacity.

In this section, we identified the relationships between a road pricing measure (the stimuli), the choice behaviour of decision-makers (the response), and the traffic system effects. The resulting stimulus-response framework is the main contribution of this chapter to this thesis, as it summarises the complex interactions between road pricing, behaviour and system performance and provides an easy to read overview for people interested in knowing more about road pricing. We will use the stimulus-response framework in Chapter 7., The framework serves as a starting point in the development of a modelling framework that can forecast the traffic effects of road pricing measures.

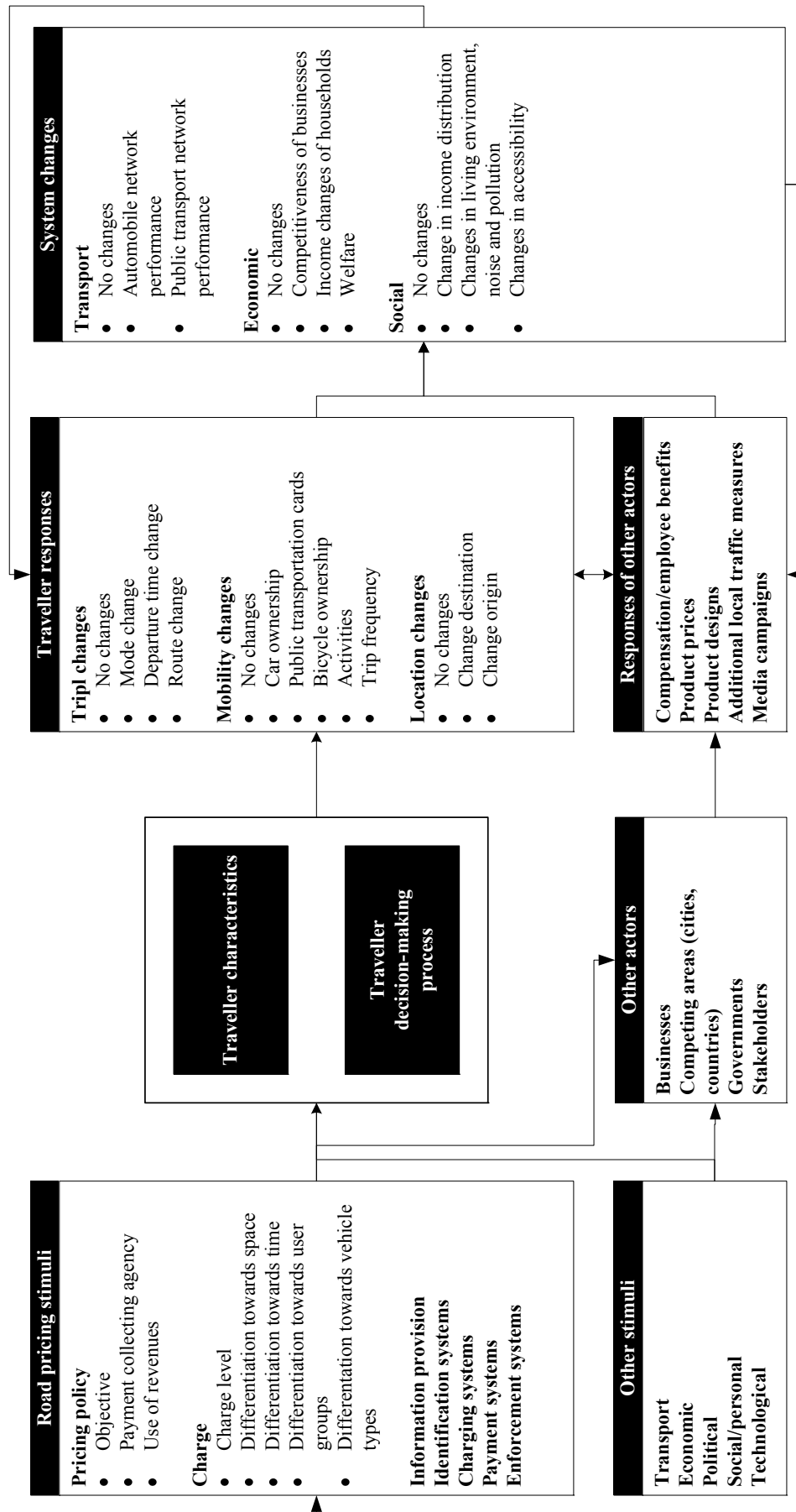


Figure 2.6: Stimulus-response framework

PART B: Behavioural responses to road pricing

This part covers the survey design and respondent characteristics. Using the data from the survey, different choice models are estimated to find the important attributes in the route, departure time and mode choice responses to time-varying road pricing. The key findings of this part are:

- Commuters are sensitive to departure and arrival time rescheduling and these sensitivities are non-linear. Commuters are more sensitive to late than to early rescheduling
- The rescheduling outside acceptable departure and arrival time bandwidths incurs additional disutility for commuters.
- Commuters have different sensitivities towards fuel cost, road pricing charges and public transport cost. Commuters are most sensitive to road pricing charges.
- There is a substantial difference in sensitivity to costs for those who are compensated by employers for travel costs and those who are not.
- A charge dummy was found to be significant, which implies that road pricing, regardless of the height of the charge, incurs disutility upon commuters. This may be affected by alternative secondary design dimensions of the road pricing measure.
- Commuters are more sensitive towards congested travel time than free-flow travel time.

3 Survey on behavioural responses

3.1 Introduction

In Part A, we presented our research objectives and scope, to investigate the behavioural responses of commuters towards time-varying road pricing. A central part of the research is to investigate the choice behaviour of commuters when faced with road pricing. In this chapter, we will elaborate on what attributes are important in the choice behaviour of commuters when presented with time-varying road pricing. Furthermore, we will present a survey we designed and conducted to collect data on these attributes, resulting in choices from commuters. The purposes of this data collection are to gain insight into the route, departure and mode choices made by commuters, to provide data that will enable the estimation of parameter values for the different attributes, and to facilitate the construction of quantitative models that can be used for prediction. In Chapters 5 and 7, the resulting data will be used to investigate mainly the departure time choice of commuters by estimating different models. In Chapter 5, however, we will first discuss some characteristics of the respondents from the survey, including some of their current travel characteristics, which will help us interpret the results of the different choice models.

A unique dedicated empirical data set has been established using a stated choice experiment with the purpose of gaining insights into commuters' responses, testing pertinent hypotheses and estimating behavioural parameters. The stated choice experiment includes commuter's route, departure time, and mode shifts in response to time and place differentiation of road pricing stimuli. Additionally, the data include travel time unreliability as a traveller's choice attribute with a new way of operationalisation in order to better represent the unreliability experienced in real life.

From a methodological perspective, we respect the repetitive nature of the commute trip in the stated preference experiments by having respondents distribute a given number of trips (10) among alternatives, rather than making a single choice. This innovative approach demonstrated that respondents appear more sensitive to road pricing and are more likely to change departure times than shown in traditional stated choice approaches. In this section, we examine the choice process of commuters in deciding what mode, departure time and route to

take in their home-to-work trip. In looking at these choice processes, we start again from the assumption that traffic is derived demand: it is needed to engage in an activity at another location. The decision to travel, but also the decision on how, when and where to travel, depends on the desired end time of the current activity and the desired start of the next (desired) activity at the (desired) location.

Chapter outline

In Section 3.2, we first discuss the general outline of the data collection, which consists of two parts: 1) a questionnaire on current travel conditions, choice alternatives and socio-demographic attributes, and 2) a stated choice experiment. In Section 3.3, we discuss the first part of the data collection, the questionnaire part, followed by the discussion on the stated choice experiment in Section 3.4.

3.2 General outline of data collection

In order to investigate the scheduling choices of commuters when time-varying road pricing is introduced, with consideration also of travel time unreliability, we need data about the choices of individual travellers in different circumstances. Since we do not have access to these kinds of data, we collected data ourselves. In the next section, we will elaborate further on this data collection. The purposes of this data collection are to gain insight into the route, departure and mode choices made by commuters, to provide data that will enable the estimation of parameter values for the different attributes, and to facilitate the construction of quantitative models that can be used for prediction.

In this section, we will present the general outline of the data collection that was necessary for the investigation of scheduling behaviour explained in the previous section. The complete process of data collection consisted of two parts: 1) a questionnaire about the respondent, his/her current behaviour and available choice alternatives and 2) a stated choice experiment in which respondents were offered different travel choice options which varied in trip characteristics. These travel options were changes organized in a way that allowed us to measure the effect of a characteristic on the choice behaviour. How to construct these alternatives such that the responses resemble ‘real’ choice behaviour is one of the most important issues in designing the data collection.

Since we are interested in how people will choose between different routes, departure times and modes when time-varying road pricing is introduced, we included choice alternatives for those situations. A more detailed description of the alternatives in the stated choice experiment will be given in Section 3.4.

Each of the alternatives in the stated choice experiment consists of different attributes which describe the alternatives in such a way that respondents can choose between them. Each alternative will consist of, at least, a departure time, a travel time, a travel cost and an arrival time. There are, in the extreme, two approaches for determining the values of these attributes: using hypothetical values or using values based on the current choice situation of respondents. In order to make the experiment as realistic as possible for respondents, we used attribute values based on the current behaviour of respondents for all attributes in the stated choice experiment. The attributes and levels for each of the four alternatives in the experiment are presented in more detail in Section 3.4.3.

Since we construct the choice alternatives based on the current travel behaviour of respondents, we need to know this current choice behaviour. For this purpose, prior to the

stated choice experiment, a traditional questionnaire was added to ask respondents about their current commute trip, the characteristics of their alternatives and some socio-demographic information. An implication of using a stated choice experiment based on the current behaviour of travellers is that the data can best be collected using a computer aided interviewing technique, so that the values in the experiment can be calculated by the computer based on answers to earlier questions. The data collection techniques are further elaborated on in Section 3.4.5.

The data collection thus consists of two parts: a questionnaire and a stated choice experiment. This data collection was, however, part of a larger data collection within the MD-PIT research project (Steg et al. (2006)). For more details about the other parts of the data collection and the results of subsequent data analyses, we refer to Tillema (2007) and Ubbels (2006), who have also used the data from this stated choice experiment in their research. We now proceed to discuss the setup of the questionnaire in Section 3.3 and the details of the stated choice experiment in Section 3.4.

3.3 Questionnaire on current travel behaviour

In this section we discuss the questionnaire part of the data collection. The questionnaire is divided into three parts. The first part contains questions about the current behaviour of the respondents, the second part about their travel alternatives and their characteristics and the third part contains questions about socio-demographic characteristics. We ask the respondents about their current choices and alternatives because these will serve as a basis for constructing choice options in the stated choice experiment. We present the most important questions of each of the three parts in more detail.

Current behaviour

The focus of our research is on commuters, so we have selected only respondents that travel from home to work by car. But we want to know more about the current choice behaviour in order to construct the choice options in the experiment. This includes:

- preferred departure time
- average travel time
- free-flow travel
- typical departure time
- trip distance

Besides the characteristics of the current travel choice of respondents, we also asked questions about some of the circumstances in which these choices were made. Particularly, we asked in detail about if and how commuters were compensated for their travel costs.

Available alternatives

We want to construct choice alternatives that make sense to decision-makers. In order to do this, we asked questions about the route, departure time and mode choice alternatives of respondents. If respondents have alternatives, we have asked them about the characteristics of these alternatives as well. Concerning the route choice alternatives, we asked about the availability of the best alternative, the change in trip distance and average travel time, and the relative frequency of use of this alternative route. In regards to the departure time choice of respondents, we asked them about the existence and size of departure time and arrival time constraints. We also asked about the availability and use of alternative modes and the travel time and costs of the using public transport (if available).

Socio-demographic characteristics

When making choices, no two individuals are exactly alike, arriving at the same decision with identical alternatives. In other words, travellers are heterogeneous, and we want to explain this heterogeneity as well as possible by including characteristics of the respondent in the choice models. For this purpose, we asked respondents questions about their marital status, children, income, education, gender, etc. The content of the stated choice experiment did not depend on these respondent characteristics, but they can be used later as explanatory variables in the choice models.

3.4 Stated choice experiment

In this section, we present the setup of the stated choice experiment. The stated choice experiment allows us to let respondents make travel choices from constructed choice alternatives. This allows us to: 1) develop choice models we can use for forecasting purposes, 2) identify the importance of each attribute in a choice alternative and 3) introduce road pricing measures that, in reality, do not yet exist. We first discuss why we included which alternatives in the experiment (Section 3.4.1) and proceed to explain why, what attributes were used and how the values of these attributes were changed in the experiment (Section 3.4.3). However, in Section 3.4.2, we first present the resulting choice screen and choice task in order to provide an overview of the entire experiment. In Section 3.4.4 we discuss the underlying experimental design and in Section 3.4.5 the data collection technique that we used to collect the responses from respondents. There exists a substantial amount of literature on the design of stated choice experiments and the analyses on resulting data. We will not discuss this literature, but refer to Louviere et al. (2000) for more information on stated choice experiments.

3.4.1 Alternatives in the experiment

The aim of the stated choice experiment is to collect data about the choices of respondents in situations where they make trade-offs between paying a road pricing fee while travelling under more preferred conditions (arrival time, travel time) versus paying less (or nothing) and facing less attractive travel conditions in terms of route, departure time and mode. In order to investigate these behavioural responses, we need to present the respondents with choice alternatives that include these behavioural responses. We thus need alternatives that differ in route, departure and mode. In the experiment, we presented each respondent with four alternatives, which include the before mentioned choice alternatives and one alternative that has preferred travel conditions, but a higher road pricing fee. The alternatives are labelled car or public transport and can be described as follows:

Alternative A: use the car and pay for preferred travel conditions

Alternative A is based on the reported preferred travel conditions; this includes the preferred arrival time and the free-flow travel time. Small deviations are created on these preferred travel conditions. The price in alternative A is relatively high.

Alternative B: use the car and adjust arrival time to avoid paying (much)

Alternative B has a lower road pricing fee than alternative A, but in return the travel conditions are less attractive. There will be more congestion, which leads to higher travel times and travel time uncertainty. Both departing earlier and later are included in this alternative.

Alternative C: use the car and adjust arrival time and route to avoid paying (much)

In alternative C, traffic conditions are also less favourable than in alternative A. In this case, respondents are provided with a detour, offering them the option of paying less (or avoid paying). In return, however, they will face longer travel times and more congestion than in alternative A. The arrival time changes are smaller than in alternative B.

Alternative D: use public transport to avoid paying (much)

In alternative D, respondents are provided with an alternative mode to using the car. This option is always a public transport option, even though currently there might not be a public transport option available to the commuter. To reduce the complexity of the experiment, we choose to only include mode shifts to public transportation, since this is most relevant for us from a transportation policy perspective.

3.4.2 Choice screen layout and choice task

In the previous section, we discussed the alternatives in a choice set. In this section, we show how the choice sets were presented to respondents. We also discuss the choice task that we gave the respondents. Each of the alternatives in the choice experiment was displayed in a table column. The alternatives themselves were not labelled, but the first attribute shown to respondents was the mode of transportation. The attributes of each alternative were displayed in rows, where similar attributes, for example travel time attributes, were grouped. On the bottom row of the choice screen, respondents could then enter their response. An example of a choice screen, with indicative values, is shown in Figure 3.1. In the experiment, the order of the alternatives did not change between choice screens.

Alternative A			Alternative B			Alternative C			Alternative D		
Mode: car			Mode: car			Mode: car			Mode: public transport		
Trip length		30 km	Trip length		30 km	Trip length		36 km	Trip length		30 km
Total travel costs		€ 5.60	Total travel costs		€ 2.90	Total travel costs		€ 2.40	Total travel costs		€ 3.50
Fuel costs		€ 2.00	Fuel costs		€ 2.00	Fuel costs		€ 2.40			
Charge		€ 3.60	Charge		€ 0.90	Charge		€ -			
Departure time		8:30	Departure time		8:00	Departure time		7:55	Departure time		7:45
Travel time between		0:30 and 0:35 min	Travel time between		0:45 and 1:10 min	Travel time between		1:00 and 1:25 min	Travel time		1:05
of which free-flow		30 min	of which free-flow		20 min	of which free-flow		5 min			
min.congestion		0 min	min.congestion		25 min	min.congestion		65 min			
max.congestion		5 min	max.congestion		50 min	max.congestion		85 min			
Arrival time between		9:00 and 9:05	Arrival time between		8:45 and 9:10	Arrival time between		8:55 and 9:20	Arrival time		8:50
Number of trips:			Number of trips:			Number of trips:			Number of trips:		

Figure 3.1: Example of choice screen layout

The choice task

The data collection is set up to investigate the choice behaviour of car commuters in their home to work trip. These home to work trips are recurrent trips that people make often. We expect that, in the decision making of commuters on how and when to go to work when a time-varying road pricing measure is introduced, commuters will not decide based on the characteristics of a single trip but, for example, on expected travel conditions and costs on a monthly basis. In general, people receive their salary once a month in the Netherlands. Commuters may, therefore, do different things on different days to lower the monthly costs of travel. In order to investigate this variability in choice behaviour, we let respondents distribute ten trips among the alternatives, rather than letting respondents choose only the preferred option. Using this approach, we expect that respondents will better take into account the repetitive nature of the home to work trip and consider the consequences of their decision-making in real life.

3.4.3 Attributes and Levels Used in the Experiment

The values of the attribute levels presented to respondents are all pivoted around the current travel conditions reported by the respondents, based on an underlying experimental design. In this section, we discuss how the attribute values were constructed. First, we will discuss how the values of different travel time components were calculated, including the departure and arrival times, and we will then put these together in a framework to demonstrate how these attributes all interact. Following the discussion of time attributes, we then present the travel cost attributes, including the road pricing fee attribute.

Travel time (car, alternatives A,B,C)

The total travel time for the car alternatives presented to respondents consists of three parts: free-flow travel time, congested travel time and travel time unreliability. This distinction is made because we expected that different travel time components might be valued differently by travellers. Here we discuss how the free-flow and congested travel times are calculated. The calculation method is the same for alternatives A, B and C, only the attribute values differ. When calculating a free-flow and congested travel time for a single trip, it is clear that the two are linked. We therefore create the two travel time attributes from a single function in which a parameter determines what part of the trip (length) will experience free-flow conditions and what part congested conditions. For the congested travel time part, we assume a speed that is one third of the free-flow speed. Adding the free-flow travel time and the congested travel time provides the total travel time for the trip. Let $\hat{\tau}_i^{\text{ff}}$ denote the free-flow travel time as reported by respondent i , and let α_{xa} be the fraction of the distance in free-flow conditions used in choice situation x . Then levels for the free-flow travel time, τ_{ixa}^{ff} , the congested travel time τ_{ixa}^c , and the total travel time τ_{ixa}^- , shown to respondent i in choice situation x for each alternative a can be computed as:

$$\tau_{ixa}^{\text{ff}} = \alpha_{xa} \hat{\tau}_i^{\text{ff}} \quad (3.1)$$

$$\tau_{ixa}^c = 3(1 - \alpha_{xa}) \hat{\tau}_i^{\text{ff}} \quad (3.2)$$

$$\tau_{ixa}^- = \tau_{ixa}^{\text{ff}} + \tau_{ixa}^c \quad (3.3)$$

The fractions α_{xa} stem from the underlying experimental design. The shortest possible travel time occurs when $\alpha_{xa} = 1$ and is equal to the free-flow travel time. The longest travel time

occurs when the trip is completely congested, i.e. $\alpha_{xa} = 0$. For alternative A, the free-flow part of the trip is higher ($\alpha_{xA} \in \{0.85, 0.90, 0.95, 1\}$) than for alternative B ($\alpha_{xB} \in \{0.65, 0.70, 0.75, 0.80\}$), while the free-flow part of the trip for alternative C is even lower ($\alpha_{xC} \in \{0.55, 0.60, 0.65, 0.70\}$).

Travel time (public transport, alternative D)

The travel time of the public transportation alternative is calculated in a different way, and it is either based on the travel time using public transportation reported by respondents in the preceding questionnaire or it is based on the reported free-flow travel time by car. If respondents are unsure about the travel time by public transportation or do not know it at all, leaving no reliable answer from the questionnaire, the free-flow travel time by car is multiplied by 1.3 and serves as the base travel time. The travel time by public transport τ_{ixD} shown to respondents is then calculated by multiplying the base travel time τ_i^b with multiplication factors ($\alpha_{xD} \in \{1.0, 1.2\}$) as shown in Equation (3.4).

$$\tau_{ixD} = \alpha_{xD} \tau_i^b \quad (3.4)$$

Uncertainty of travel time

As mentioned earlier, we show three travel time components to respondents. Travel time unreliability is the third components we want to include. Including travel time unreliability in a stated choice environment is somewhat of a challenge. In reality, travellers will not know their travel time and arrival time at the moment they decide to leave, or start their journey. They may have some expectation about the travel time and its distribution based on experiences and information. As soon as we present a travel time to respondents as a fixed number, we reduce the unreliability that occurs in reality. Different approaches have been used to introduce uncertainty into the choice task, for example by presenting more travel times per alternative drawn from an underlying distribution. We show some examples in Appendix A. Our view, which we cannot substantiate, is that this method does introduce some uncertainty, but not at the level at which travellers experience uncertainty in reality. We therefore used an approach that makes the travel time and, as a consequence, the arrival time, unreliable between boundaries. We presented respondents with a shortest and a longest travel time, between which any travel time has an equal chance of occurring. The difference between the shortest and longest travel time is our travel time unreliability attribute. As a base for this travel time unreliability attribute, we use the difference between reported mean travel time, $\hat{\tau}_i$ and the reported free-flow travel time, $\hat{\tau}_i^{\text{ff}}$. We assume that this value is an indicator for the experienced variability in travel time for that respondent. Using this value, we calculate an unreliability bandwidth, ν_{ixa} , which is the calculated difference multiplied by a certain factor γ_{xa} :

$$\nu_{ixa} = \gamma_{xa} (\hat{\tau}_i - \hat{\tau}_i^{\text{ff}}) \quad (3.5)$$

This unreliability is then presented to the respondents in the form of a shortest travel time, equal to τ_{ixa}^- (see Equation (3.3)), and a longest travel time, $\tau_{ixa}^+ = \tau_{ixa}^- + \nu_{ixa}$. Since alternative A has the preferred travel conditions, the unreliability factors are small ($\gamma_{xA} \in \{0.2, 0.4, 0.6, 0.8\}$). For alternatives B and C, the factors are larger, namely $\gamma_{xB} \in \{0.8, 1.0, 1.2, 1.4\}$ and

$\gamma_{xC} \in \{0.6, 0.8, 1.0, 1.2\}$, respectively. For alternative D (the public transportation alternative), we assume the uncertainty of travel time to be zero, i.e. $\gamma_{xD} = 0$.

Departure and arrival time

Now that we have discussed all the travel time components, we need to add departure and arrival times. The arrival time in the experiment is an attribute that is systematically changed, the departure time then results from arrival time and travel time. The arrival times in the experiment are based on the preferred arrival time for each respondent i , PAT_i , which is computed based on the reported preferred departure time from the questionnaire, PDT_i , and the reported free-flow travel time:

$$PAT_i = PDT_i + \hat{\tau}_i^{\text{ff}} \quad (3.6)$$

The earliest arrival time, AAT_{ixa}^- , presented to respondent i in choice situation x for alternative a is computed by making deviations δ_{xa} from their preferred arrival time, that is:

$$AAT_{ixa}^- = PAT_i + \delta_{xa} \quad (3.7)$$

In alternative A, the arrival times have small deviations from the preferred arrival time ($\delta_{xA} \in \{-10, -5, 0, 5\}$ minutes from preferred arrival time), whereas in alternative B these deviations are much bigger ($\delta_{xB} \in \{-50, -30, -10, +10\}$ minutes from preferred arrival time). The deviations for alternatives C and D are $\delta_{xC} \in \{-30, -20, -10, 0\}$ minutes, and $\delta_{xD} \in \{-30, -10, +10, +30\}$ minutes from their preferred arrival time, respectively. Using the travel time unreliability attribute, we then also compute the latest possible arrival as follows:

$$AAT_{ixa}^+ = AAT_{ixa}^- + v_{ixa} \quad (3.8)$$

The departure time of the trip shown to respondents is also calculated from the earliest arrival time AAT_{ixa}^- and the total travel time:

$$ADT_{ixa} = AAT_{ixa}^- - \tau_{ixa}^- \quad (3.9)$$

We have covered all the time attributes in the experiment separately. Figure 3.2 shows how the different time components are related in together presenting a time-consistent trip alternative. From the questionnaire, we have used the free-flow travel time, the mean travel time and the preferred departure time as reported by respondents. Since these are different for every respondent, all the time attributes are different for each respondent and tailored to their current circumstances.

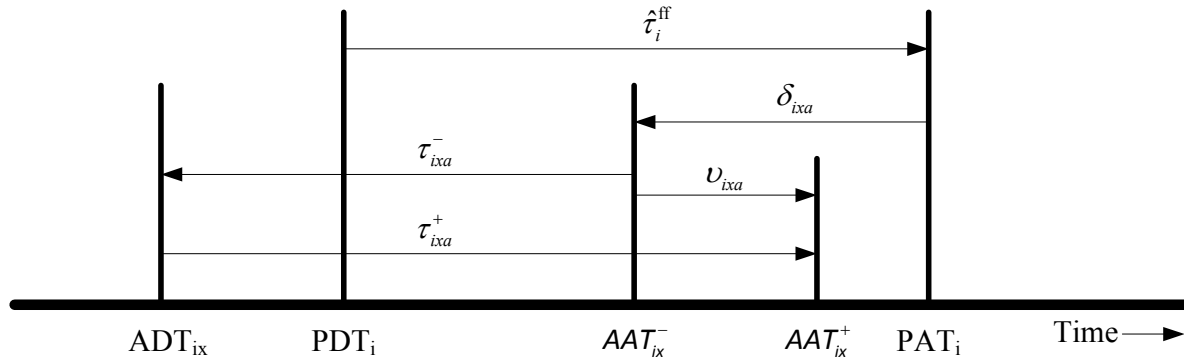


Figure 3.2: Relationship Between Different ‘Time’ Attributes

Figure 3.2 can best be read as follows. Starting at the preferred departure time, we calculate the preferred arrival time, using the free-flow travel time, where the data are answers from the questionnaire. We then create deviations to the preferred arrival time, create a shortest travel time and a travel time unreliability bandwidth. Together, these attributes create the actual departure time, the longest travel time and the latest arrival time.

Trip length

Since we are interested in possible route changes to avoid paying a road pricing fee or lower the amount, we change the trip length for alternative C. Changing the trip length also changes the road pricing fee and fuel costs shown to respondents. Alternative C is a route alternative in which we present respondents with an option to avoid paying by taking a detour. This means that the distance of this trip is always longer than for the other alternatives. The trip length attribute of alternative C has two levels, computed by multiplying the reported trip length from the questionnaire with a factor of 1.2 or 1.4.

Travel costs

The travel costs presented to respondents in the experiment consist of fuel (car) or fare (public transport) costs and a road pricing fee. The only attribute that is systematically changed is the road pricing fee. The other cost components serve as reference costs. All cost attributes are calculated based on the trip length in the experiment. In case a respondent reports getting a complete compensation for commute costs from his/her employer, the fuel and public transport costs are set to zero. The road pricing fee in the experiment is assumed to be a distance based fee, partly because of the policy relevance it has in the Netherlands. The levels of fees are, to some extent, also based on prices mentioned in Dutch road pricing proposals. Alternative A has the highest prices (8, 10, 12, 14 ct/km) but the best conditions. Alternative B has lower prices (3, 4, 5, 6 ct/km) and alternative C has the lowest prices (levels 0, 1, 2, 3 ct/km).

In this section, we have now discussed all the attributes of the stated choice experiment and how their values are determined. In Table 3.1, we present a summary of the attributes that are systematically changed in the choice experiment.

Table 3.1: Summary of attributes and levels for each alternative A, B, C and D

Attribute	Calculation of level by	Alternative			
		A	B	C	D
Arrival time	deviation from PAT [min]	-10	-50	-30	-30
		-5	-30	-20	-10
		0	-10	-10	10
		5	10	0	30
Travel time:	percentage of trip length in free-flow	85	65	55	
		90	70	60	
		95	75	65	
		100	80	70	
Uncertainty:	percentage of difference between reported mean and free-flow travel time	20	80	60	
		40	100	80	
		60	120	100	
		80	140	120	
Road pricing fee:	Kilometre charge [cent/km]	8	3	0	
		10	4	1	
		12	5	2	
		14	6	3	
Trip length	reported length [multiplication factor]			1.2	
				1.4	
Travel time public transport	reported travel time (car or PT) [multiplication factor]				1
					1.2

3.4.4 Experimental design

In Section 3.4.3, we presented the attributes and their values for the different alternatives, but we have not yet discussed how the attribute values are changed (other than systematically). This is captured by the underlying experimental design, which we will discuss in this section. We have a partly labelled experiment in which the alternatives have the label car or public transportation. Within the car alternatives, however, no further labelling has been applied. The four alternatives consist of different attributes that are based on the current behaviour of respondents, as discussed in the previous sections. Each of the attributes has either 2 (2 attributes) or 4 (13 attributes) levels. Using four level attributes, we assume that non-linear effects for these attributes cannot be dismissed beforehand.

We assume that all the interaction effects between attributes are zero, leaving us with only having to estimate the main effects. In this case, the total amount of degrees of freedom is 42. We want to construct an orthogonal design, which implies that the minimum number of treatments, in order for the design to be balanced, must be dividable by 2 and 4, but also larger than 42. This means the smallest useable design has 44 treatments. This design was constructed by John Rose of the Faculty of Economics and Business at the University of Sydney.

We do not want our respondents to face 44 choice sets and we therefore adopted a blocking strategy of four blocks with 11 choice sets each. Each respondent is assigned a block

randomly, and the order of the 11 choice sets within a block is randomized as well. We planned to conduct the survey under 1000 respondents, ideally leaving us with 250 complete designs of data collected.

The levels for each attribute are evenly spaced (see Table 3.1). After applying the levels on the current trip characteristics of a respondent, however, the actual data presented to respondents are no longer uncorrelated. Travel time and trip distance are, for example, naturally correlated.

3.4.5 The data collection technique

For the data collection, we contracted a large Dutch data collection agency, using their panel of over 200,000 respondents who receive approximately one survey per month. These respondents are carefully chosen from different demographic and socio-economic variables and all respondents are familiar with the CAI technique. The complete data collection was programmed using the software of the data collection agency, including all kinds of consistency checks on input from respondents. Respondents were contacted by email, including a link to a download site. The survey is downloaded to the respondent's computer, so that a respondent can pause.

Since we want respondents that use their car for home-to-work trips and also face congestion on a regular basis, we selected working respondents, which drive to work by car two or more times per week and face congestion of 10 or more minutes for at least two times a week. This resulted in a total of about 6800 possible respondents. Some initial analyses of these respondents showed that we had a relatively low number of women and lower income groups. We therefore decided not to take a random sample, but to over sample the lower income groups. We can, however, weigh each respondent to get representative results for the Netherlands. The data were collected in a three-week period in June 2004 and consist of 1115 respondents. In the next chapter, we will discuss the characteristics of the respondents in more detail.

3.5 Conclusions

In this chapter, we discussed the need for collecting new data and the setup of the resulting data collection that was conducted in our research. We found that the departure time choice behaviour of commuters depends on the activities at the home and work side of the trip. Changing the departure time will affect the utility of both activities, as well as the disutility of travel. From this realisation, we adopted a scheduling delay approach for modelling departure time choice, in which we recognise that both departure time and arrival time constraints can cause scheduling delays. We also find that the travel time unreliability, which is often not taken into account, may be an important factor in departure time choice.

In order to research and model how commuters make departure time decisions with time-varying road pricing measures, we need data on the choice behaviour of individuals. We do not have these data and such data were therefore collected within this research. Since there are no time-varying road pricing measures in operation in the Netherlands, we used a stated choice experiment to generate the choice data of individuals.

In the stated choice experiment, we included travel time unreliability. Including travel time unreliability in a stated choice environment is not trivial. The key issue with unreliability is that people do not know beforehand, while in stated choice experiments, all relevant attributes of an alternative are assigned a specific value (and are thus known to the respondent). Letting

respondents truly feel travel time unreliability when deciding between alternatives is difficult and there is certainly no consensus yet on the best research method. Our experiment contributes to this research, since we adopted a bandwidth presentation of travel times. Within this bandwidth it is unknown what travel time the respondent would experience if they choose that option. By changing the bandwidth size, we can assess the influence of travel time unreliability on departure time choice. Some of the other research methods include travel time unreliability by drawing travel times from a distribution. In this case, respondents see several travel times that could occur but all of them are fixed, which may reduce the uncertainty in the decision making as compared to reality. In Chapter 6, we will investigate how sensitive respondents are to travel time unreliability and how travel time unreliability can best be included in the utility function.

A second point in which the stated choice experiment deviates from ‘normal’ practise is that we let respondents distribute 10 trips among the alternatives, rather than letting them choose one. The commute trip is a recurrent trip that people make many times each month. The choices about the commute trip are likely made while considering more than one trip. This may also result in commuters making different choices in identical situations, for example to reduce costs. Distributing 10 trips among the alternatives supports this, but if this choice behaviour does not occur, respondents can still assign all trips to 1 alternative. In the next chapter, we will discuss how respondents handled the choice task.

In the next chapter, we investigate the socio-demographic characteristics of the respondents in our data collection, as well as some of their responses to the questionnaire and the stated choice experiment. These analyses will help with the interpretation of model estimation results in the succeeding chapters.

4 Respondent analyses

4.1 Introduction

In this chapter, we investigate the current commute trip characteristics and some of the demographic characteristics of the respondents, the results of the data collection presented in the previous chapter. In total, 1115 useable completed surveys were conducted. It is important to investigate both the behaviour and the characteristics because this will help us interpret the results of choice model estimations in the succeeding chapters. Furthermore, the socio-demographic characteristics can explain the heterogeneity in behavioural responses, which we want to investigate. Lastly, when using the choice models in forecasting, we would need to correct for differences between our sample and the population we are modelling.

The objective of this chapter is to provide insights into the characteristics of the respondents and the conditions of their current home to work trip. These insights will help interpret choice model results in later chapters. Provided that sufficient heterogeneity exists in the personal characteristics of respondents, we will also be able to explain potential heterogeneity in choice behaviour by personal characteristics.

In the data collection, the objective was not so much to have a representative sample, but rather to have enough spread in socio-demographic characteristics to be able to capture and explain possible heterogeneity in choice behaviour. One of the issues is to see how the distributions of choices and characteristics of respondents compare to representative data from other sources. We will thus compare the data from our respondents to other data sources on mobility in the Netherlands. We will use histograms, averages and other statistical measures for these comparisons.

This chapter contributes to this thesis in that the analyses in the current departure time choice of respondents shows that the respondents are currently leaving earlier than preferred, but tend to arrive at their preferred time. Also, respondents report that acceptable bandwidths for departing and arriving exist, where arriving late is dominant. Another interesting contribution of this chapter is the analysis of how respondents have distributed the 10 trips among the 4 alternatives. We will show that, as we expected, a large part of respondents distribute the trips

over more than one alternative, but also that respondents are able to identify a preferred alternative, to which they assign most of these trips. Respondents are thus not indifferent to the choice alternatives presented to them and seem able to trade-off the alternatives when asked to distribute 10 trips.

The outline of this chapter is as follows. In Section 4.2 we present the socio-demographic characteristics of respondents, including income, gender, and education distributions. In the next section, we then present the characteristics of the current home to work trip of respondents and we investigate some relations between these characteristics and the socio-demographic characteristics of the respondents. In Section 4.4, we then investigate the possibility of identifying different types of strategies used by respondents to distribute the 10 trips in the stated choice experiment.

4.2 Socio-demographic characteristics of respondents

We would like to know the extent of heterogeneity among commuters in their behavioural responses towards road pricing. In later chapters, we may use some of the socio-demographic characteristics to better explain the choice behaviour of our respondents. In this section, we will analyse the socio-demographic characteristics of our respondents and will use two other data sources to identify differences between our sample, a representative sample of travellers in the Netherlands and a survey on drivers in congestion in the Netherlands.

In 2006, the Ministry of Transport, Public Works and Water Management performed a study, Rijkswaterstaat Adviesdienst Verkeer En Vervoer (2006), to investigate the socio-demographic profile of drivers in congested traffic conditions. This source is interesting because it addresses almost the same target group of travellers. While we have limited our scope to commuters experiencing congestion, this survey includes other travel purposes and even freight as well. The data were collected in nearly the same period as our data. According to that study, car drivers present in congested traffic conditions have the following characteristics:

- 74% are between 25 and 55 years old;
- 67% are male;
- 32% have a higher education (HBO-WO);
- 82% are employed;
- 68% report making a commute trip;
- their average commute trip is 32 kilometres;
- 73% have fixed working hours;
- 42% drive 10,000 to 20,000 kilometres per year.

The second source of data comes from Statistic Netherlands (CBS), who have access to multiple sources of data on the population and mobility behaviour. One of these is the annual national mobility survey.

4.2.1 Gross annual household income of respondents

The household income of a respondent may be important in explaining choice behaviour. Higher income groups are likely, for example, to be less sensitive to the cost of road pricing than low income groups. In order to test this, we need low and high income travellers in our sample. Furthermore, if we conclude that we only have high income respondents, then we can

expect to find, for example, higher value-of-time outcomes from our choice models than are normally found in the Netherlands.

The income levels of respondents are measured by their gross annual household income. This income measure is used because the respondents were part of an internet interview panel of which this information is frequently asked and updated. Figure 4.1 presents the income distribution of our respondents.

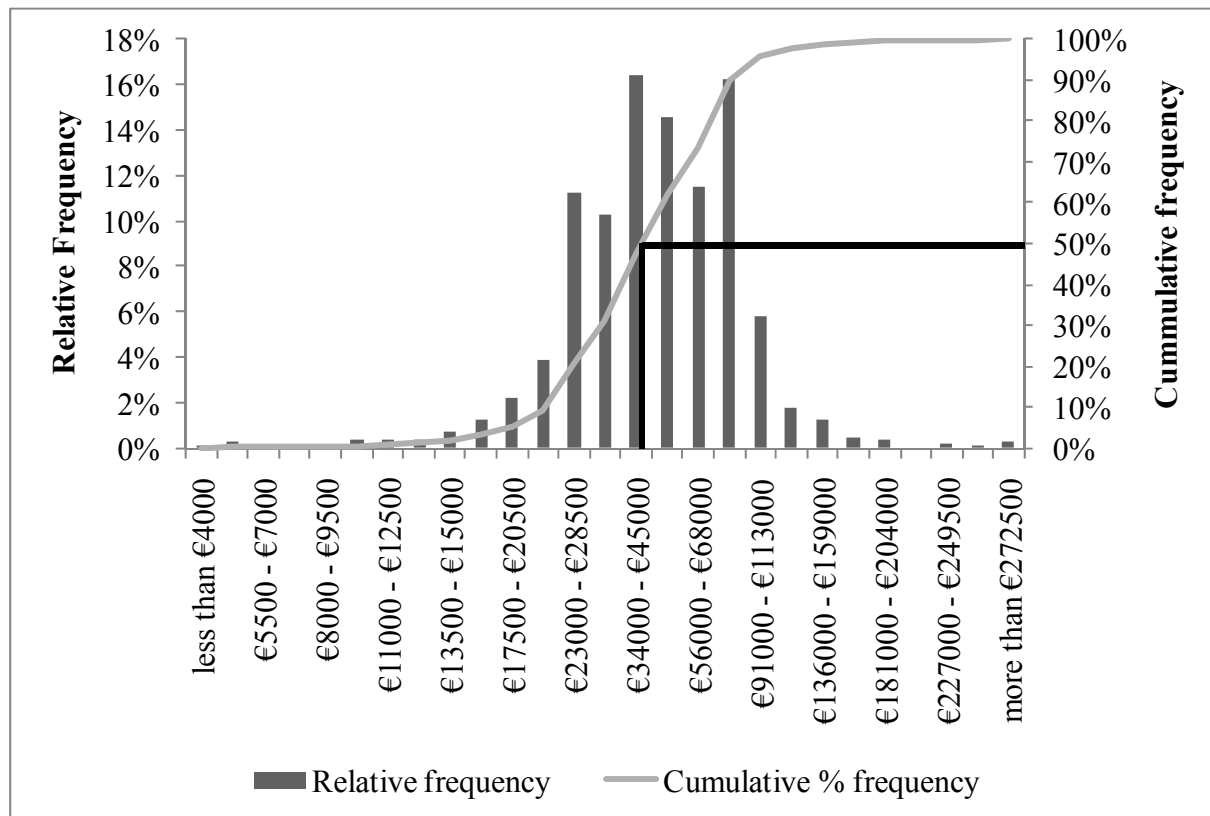


Figure 4.1: Gross annual household income distribution of respondents (N=1115)

The average annual gross household income in the Netherlands was 51,300 euro in 2006 (Statistics Netherlands (2008)). The average annual income in our sample is 54,920 euro, which is only marginally higher than the national average income. A somewhat higher average gross household income in our sample would be expected since it only includes people that work. We also only include working people that travel to work by car and face congestion; this group is likely to have a higher average income than the total population of workers. Since income levels are similar to the national average, we expect that income will not affect value-of-time estimates in this research. Looking solely at this aspect, they should be in line with values found in the Netherlands.

4.2.2 Age distribution of respondents

The age of respondents may be a factor that can explain heterogeneity of respondents in, for example, sensitivities towards time, costs and rescheduling of trips. It is likely that age should be combined with other life phase variables, such as having children, in order to assess the effect of age alone.

Figure 4.2 displays the age distribution of the respondents in our sample. Since we only include working people in our data collection, the age distribution is not representative for the

Netherlands. We did not consider including commuters over 65 years old in our sample, the retirement age in the Netherlands. The younger people, in the age group 18-25, have a small share. In our sample, 82.5% of respondents are between 25 and 55 years old, which is higher than the 74% average among drivers in congestion (Rijkswaterstaat Adviesdienst Verkeer En Vervoer (2006)). This difference is to be expected, since we do not consider people over 65.

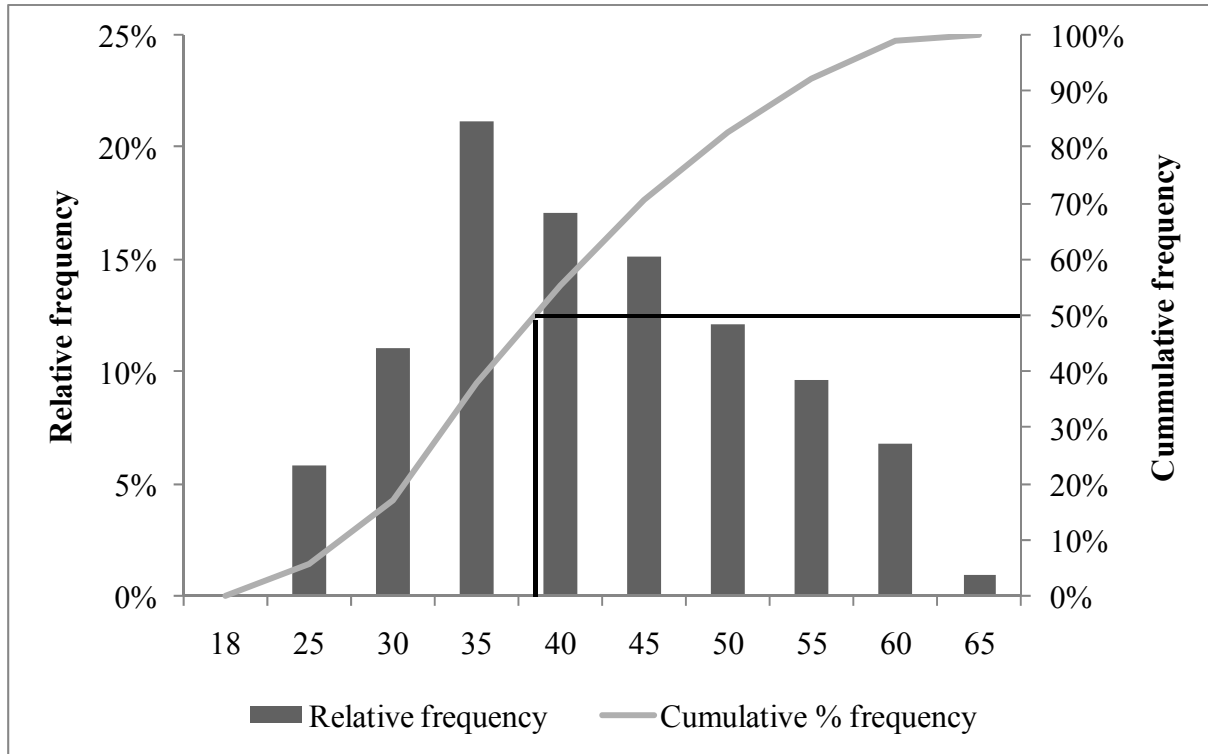


Figure 4.2: Age distribution of respondents (N=1115)

It seems that we have a slight underrepresentation of younger people and we are missing commuters over 65 years old in our sample. We do have enough spread in respondent age to investigate the role of age in explaining heterogeneity.

4.2.3 Gender distribution of respondents

Other studies on travel choice behaviour, for example Brownstone et al. (2003), found that males and females have different value-of-time and different underlying sensitivities towards time and costs. In trying to explain the discovered heterogeneity in choice behaviour, gender can thus be an important factor.

In our dataset, about 76% of the respondents are male, which is more than the 67% found by the Rijkswaterstaat Adviesdienst Verkeer En Vervoer (2006) congestion study. This difference is again as expected, since we only consider work trips in our data collection. Both the share of women in the work force and the share of women using the car are expectedly lower in reality. In the screening of respondents, we have tried to oversample lower income females to better represent this group. The median income levels of male and female respondents in our sample are equal, while the average income levels only differ slightly (55,718 for male and 52,359 for female).

4.2.4 Level of education of respondents

As with previous socio-demographic characteristics, the level of education may explain some of the heterogeneity in behavioural responses towards road pricing. The level of education

may, for example, be some proxy for the type of jobs respondents have. Aside from income levels, this may, for example, result in more flexible working hours, different travel time sensitivities, etc.

In the questionnaire, we asked respondents about their level of education, distinguishing six levels. The distribution of levels of the highest level of education completed by respondents is presented in Figure 4.3. The meaning of the different Dutch abbreviations is given in Table 4.1.

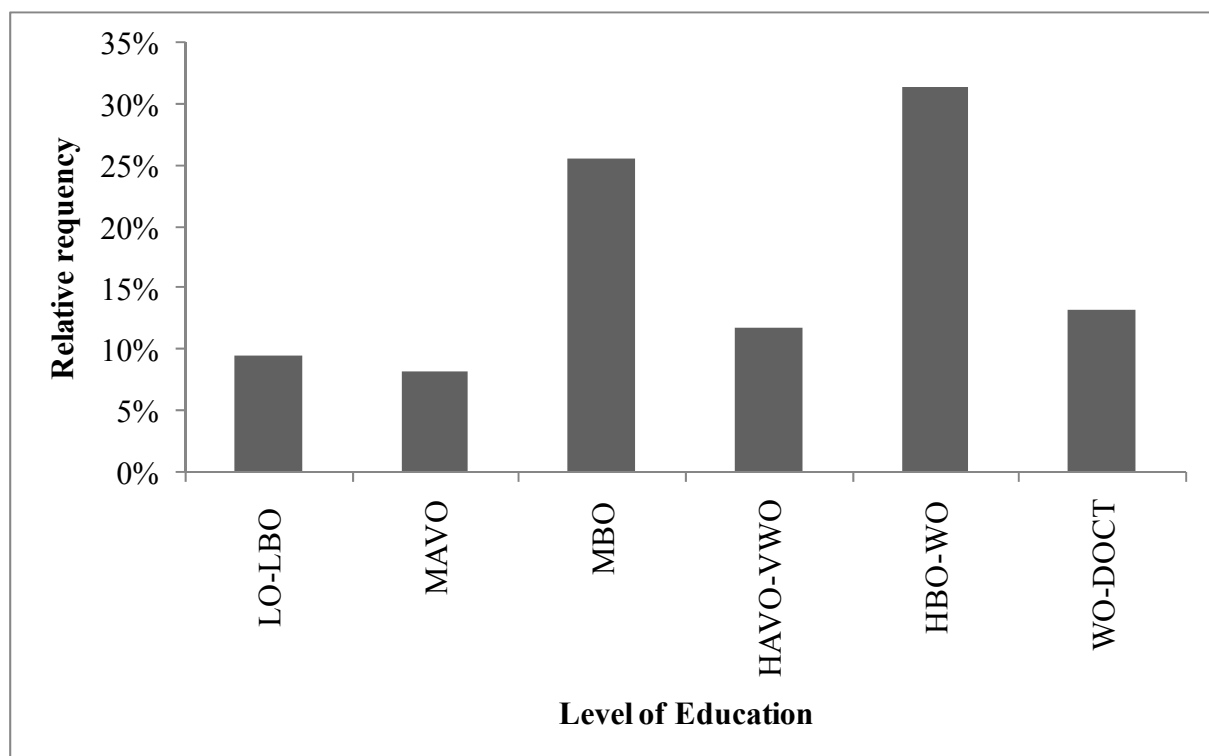


Figure 4.3: Level of highest completed education distribution of sample (N=1115)

Table 4.1: Abbreviations of levels of education and their meaning

Abbreviation	Explanation
LO-LBO	Lowest level secondary school / lowest level professional education
MAVO	Mid level secondary school
MBO	Mid level professional education
HAVO-VWO	Highest level secondary school
HBO-WO	Highest level of professional education / University (bachelor)
WO-DOCT	University (master)/ Doctoral program

About 31% of our respondents have a level of education of HBO-WO, which is almost equal to the 32% reported by Rijkswaterstaat Adviesdienst Verkeer En Vervoer (2006).

Table 4.2 presents a combined overview of respondent socio-demographic characteristics. From this table, it is clear that the women in our sample are, on average, younger and have a somewhat lower household income. Women with a lower level of education, however, tend to

have a higher household income than men with a lower level of education. Also, respondents with a higher level of education tend to be younger.

Table 4.2: Combined socio-economic characteristics of respondents (N=1115)

Values		
Row Labels	Average gross household income	Average age
male	55718	40.61
LO-LBO	37987	43.14
MAVO	48465	45.18
MBO	45816	40.32
HAVO-VWO	64568	41.44
HBO-WO	59726	39.28
WO-DOCT	78163	38.43
female	52359	37.83
LO-LBO	42192	40.46
MAVO	53170	44.59
MBO	40777	36.05
HAVO-VWO	46394	36.64
HBO-WO	56471	38.72
WO-DOCT	69436	34.90
Grand Total	54920	39.95

It seems that the variation within groups presented here is larger than the variation between groups. We conclude that there exists sufficient spread in level of education in our sample in order to investigate its contribution in explaining heterogeneity.

4.2.5 Departure and arrival time constraints

We are interested in the departure time choice behaviour of commuters when introducing road pricing. Commuters may, however, choose their departure and/or arrival time only to a limited extent. There may be constraints at both the departure and arrival side of the trip. As a result of road pricing, these constraints may change; employers might make working hours more flexible and the opening hours of day care centres may be extended, for example. We can explicitly take the constraints into account in the choice models. By doing so, we can explain heterogeneity and can forecast changes in behaviour if constraints change.

The departure and arrival time constraints of respondents are presented here as part of their socio-demographic characteristics because we assume that these characteristics depend predominantly on the household organisation and employer constraints. On the other hand, we might also interpret these constraints as part of the trip characteristics, which are presented in the next section.

In the questionnaire, we asked respondents several questions about their ability and willingness to depart from home or arrive at work earlier or later than certain times. In this section, we will first present the departure time constraints of our respondents, followed by the arrival time constraints.

The upper part of Table 4.3 shows the presence of departure time constraints at the home side. It appears that 73.2% of respondents can depart from home when they want and do not

experience any departure time constraints. Of the respondents that have departure time constraints, 56.2% cannot depart earlier than a specific time, while 53.8% cannot depart later than a specific time.

Table 4.3: Presence of home departure and work arrival time constraints of respondents

		Frequency	Percent
Depart	I can depart from home when I want	816	73.2
	I need (want) to depart within certain time limits	299	26.8
	Total	1115	100.0
Arrive	I can arrive when I want	384	34.4
	I need (want) to arrive within certain limits	731	65.6
	Total	1115	100.0

In the lower part of Table 4.3 we present the presence of arrival time constraints at the work side. It appears that many more respondents have arrival time constraints compared to departure time constraints, namely 65.6% compared to 26.8%. Of the respondents that have work arrival time constraints, 27.4% cannot arrive before a specific time and 83.4% cannot arrive after a specific time. This makes arriving after a specific time the most common constraint, experienced by 54.7% of respondents.

Having arrival time constraints shows significant correlation with gender (female), implying that women are more likely to have such constraints. It is negatively correlated with level of education and household income. This means that respondents with a higher education and/or higher income are more flexible in choosing when to arrive at work.

The heterogeneity in having departure time and arrival time constraints influences the ability of choosing a departure time and can therefore be important to take into account in the departure time choice models. In Section 5.3.2, we will use the departure and arrival time constraints in some departure time choice models.

4.3 Current home to work trip characteristics

We have asked our respondents to report typical characteristics of their current home-to-work trip. These current characteristics are used to determine the values of different attributes shown to respondents in the stated choice experiment in order to create choice alternatives that respondents can recognise. In this section, we present the travel times reported by respondents, both free-flow and average travel times. We also present the distributions in preferred departure and arrival times in relation to their current departure and arrival time and the bandwidths in acceptable departure and arrival times. These analyses show how much our respondents are currently deviating from their preferred behaviour and how much room exists to change departure and arrival times.

4.3.1 Time characteristics of the home to work trip

One of the important attributes in the stated choice experiment is trip duration. The travel times shown to respondents in the experiment are based on their current free-flow travel time. The travel time bandwidth shown in the stated choice experiment is based on the difference between the mean and free-flow travel time reported by respondents in the questionnaire. Figure 4.4 shows the distributions of reported free-flow and mean travel times of respondents' commute trips.

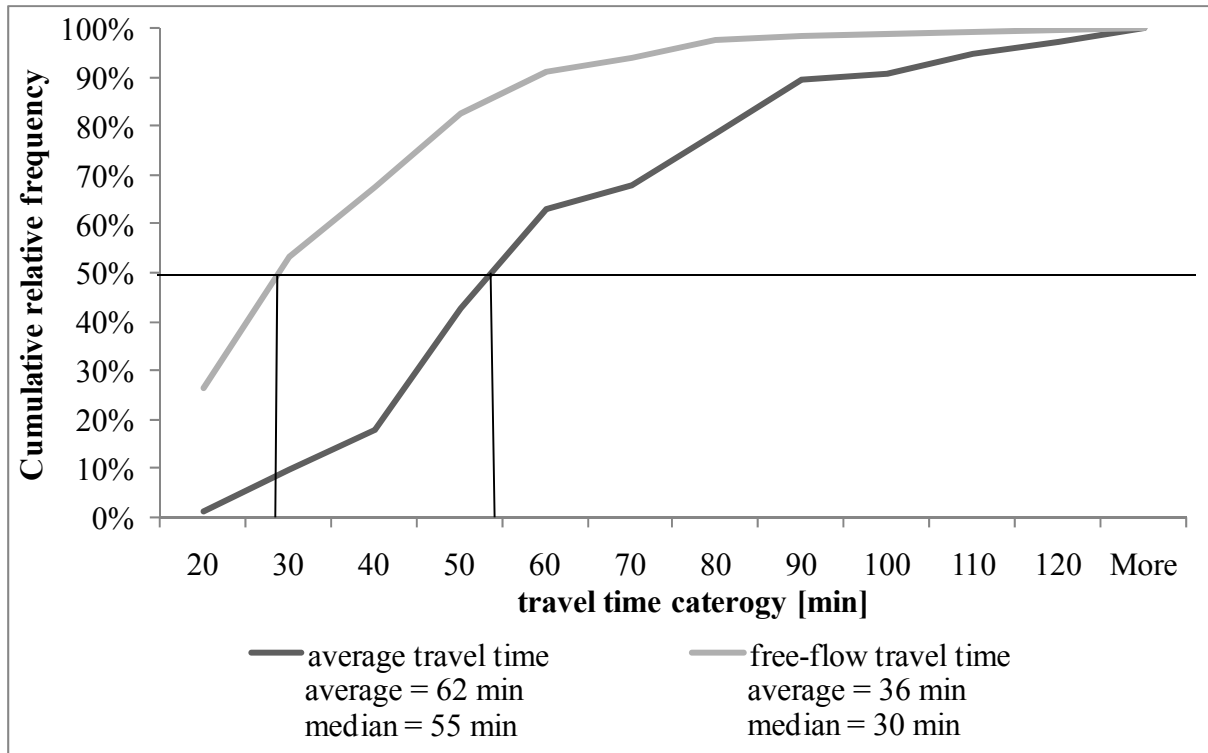


Figure 4.4: Reported free-flow and mean travel time distributions of respondents' commute trips

The average reported mean travel time is about 62 minutes, the average free-flow travel time about 36 minutes, which results in an average reported delay of 26 minutes, nearly half an hour. This is a rather substantial delay, in both an absolute and a relative sense. Since we selected respondents who experience delays of more than 10 minutes, the high average delay is not representative for the Netherlands. Also, respondents are likely to overestimate their delays in these types of questionnaires (see for example Van Amelsfort and Bovy (2000)). Rijkswaterstaat Adviesdienst Verkeer En Vervoer (2006) report delays of 25 minutes for travellers in congestion with a free-flow travel time of 30 minutes and a trip distance of 50 kilometres.

Besides travel time, the home departure and work arrival times of respondents provide important information about the choice situation of respondents. We can compare the preferred departure and arrival times with average departure and arrival times, which gives insight into how much our respondents have already deviated from their preferred travel option. This is presented in Figure 4.5 and it shows that our respondents tend to leave significantly earlier than preferred (on average approximately 20 minutes), but they tend to arrive on-time or very little later than preferred (on average 6 minutes). When looking at commute trips to work, this finding is to be expected and is in line with the finding presented in Figure 4.5, where arrival times are found to be more constrained for our respondents than departure times.

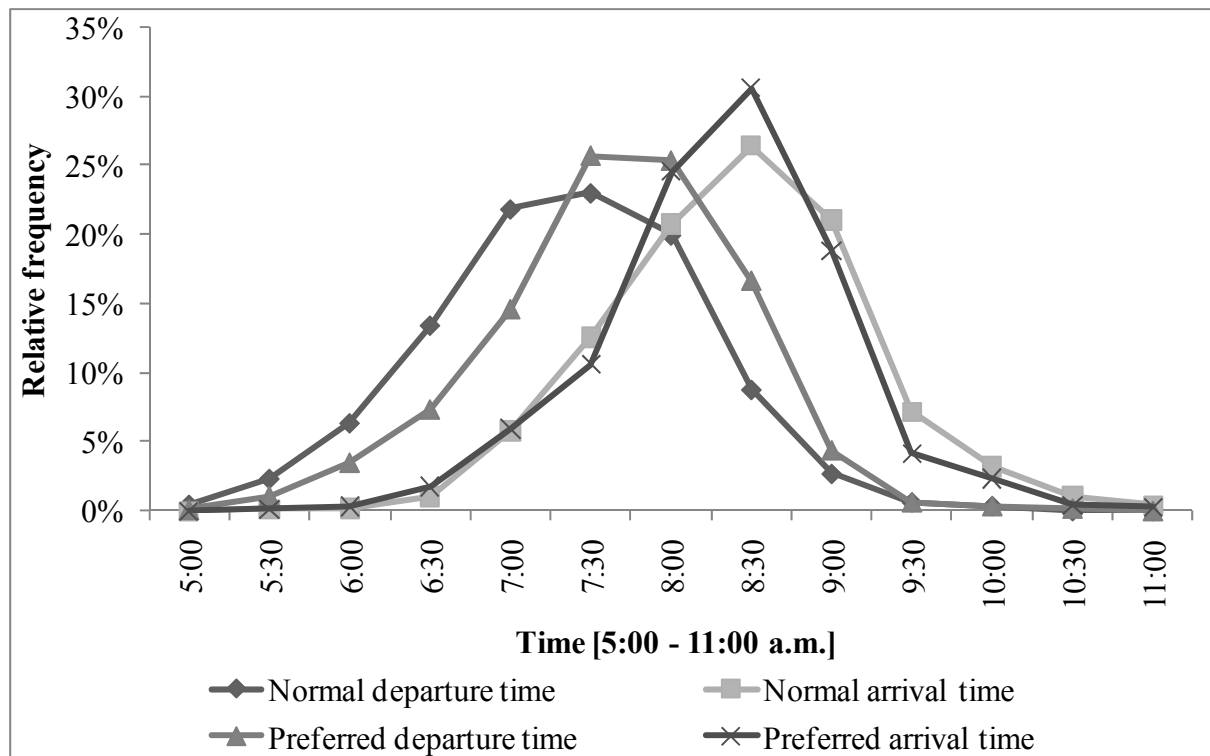


Figure 4.5: Actual and preferred home departure and work arrival times of respondents

In succeeding chapters of this thesis, we will use the preferred arrival and departure times reported by the respondents to calculate scheduling delay components that were presented in the stated choice experiment. There seems to be enough spread in preferred departure and arrival times to also investigate whether or not heterogeneity in rescheduling can be explained by taking into account the preferred departure and arrival time.

4.3.2 Compensation of commute costs

It is not uncommon in the Netherlands to be compensated for commute costs by the employer. Tax regulations allow for this and compensation can take different forms, ranging from no compensation to getting a company car. As a result of road pricing, the costs of travelling for commuters and their households will most probably change. If commuters are compensated for their commute costs, they may also be compensated for the road pricing charges. Also, the level of road pricing fee may be such that the relative cost increase for commuters is small or large, or something in between. This can affect the choice behaviour of commuters. It is therefore important to understand what the current travel costs are and to know who pays these costs.

In the stated choice experiment, we only include fuel costs and a road pricing fee. The fuel costs are based on the trip distance and fuel type of the car. We did not directly ask respondents about their home to work trip costs. We did, however, ask questions about who bears the costs of this trip. Figure 4.6 shows that almost 45% of respondents state that the employer compensates/reimburses all of their commute costs, while another 45% of respondents state that the employer pays part of the costs. These high levels of cost compensation may have substantial effect on the effectiveness of road pricing if employers will also be compensating the road pricing charges.

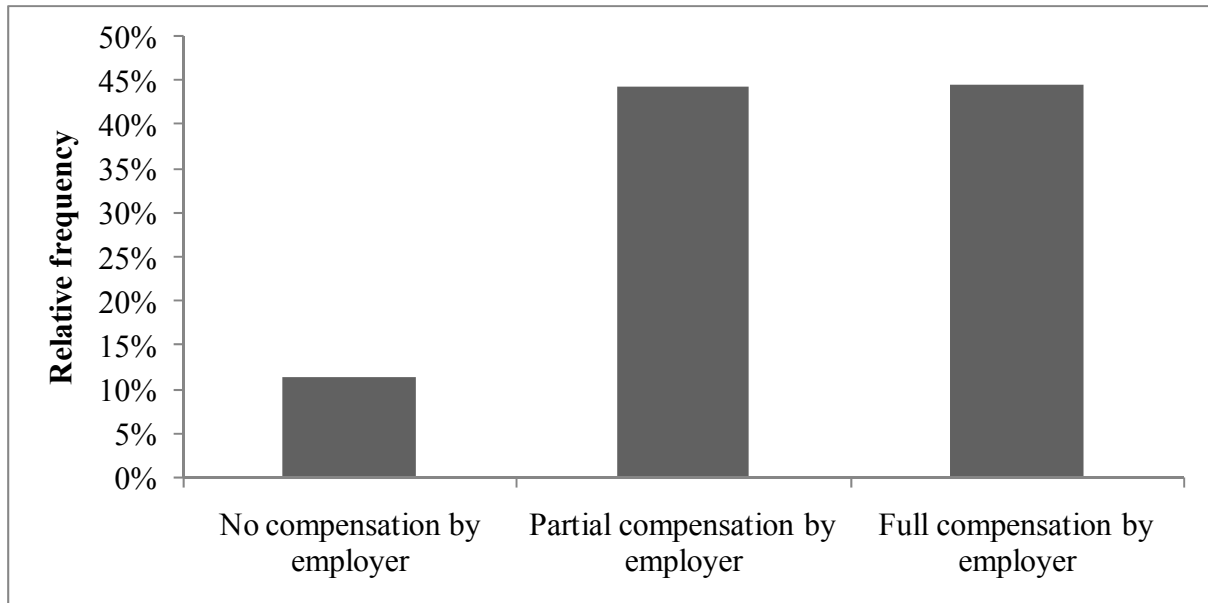


Figure 4.6: Commute cost compensation by employer (N=1115)

In the stated choice experiment, the fuel costs presented to respondents are set to zero if the costs are fully compensated by the employer. For the road pricing fee, however, we assume that there will be no compensation, or that the presented fee is the remainder after deduction of some compensation. In the choice models in succeeding chapters, we can use cost compensation interactions to see if commuters that are currently compensated for travel costs have different sensitivities towards road pricing fees.

4.4 Some analyses of responses to choice task

As presented in Section 3.4.2, the respondents were asked to distribute 10 trips among the four alternatives, rather than choosing a single option. In this section, we show how respondents addressed this choice task. We are interested in knowing whether respondents applied specific patterns in their assignment of trips to alternatives, such as, for example, by always assigning 10 trips to a single alternative only or by distributing the 10 trips over the 4 alternatives as evenly as possible (e.g. 3-3-2-2). Distributing 10 trips among the alternatives can be done in many combinations, which makes the analyses somewhat complicated.

About 40% of the respondents always assign 10 trips to a single alternative only. About 65% of respondents assign 10 trips to 6 or more of the 11 choice tasks they were presented with. Figure 4.7 shows the relative frequencies of respondents assigning the 10 trips to 1, 2, 3 or 4 of the alternatives they were presented with. A large group among the respondents do *not* assign 10 trips to one alternative, which is what we expected and which was the reason for adopting a 10-trip distribution task rather than the usual single-trip choice task.

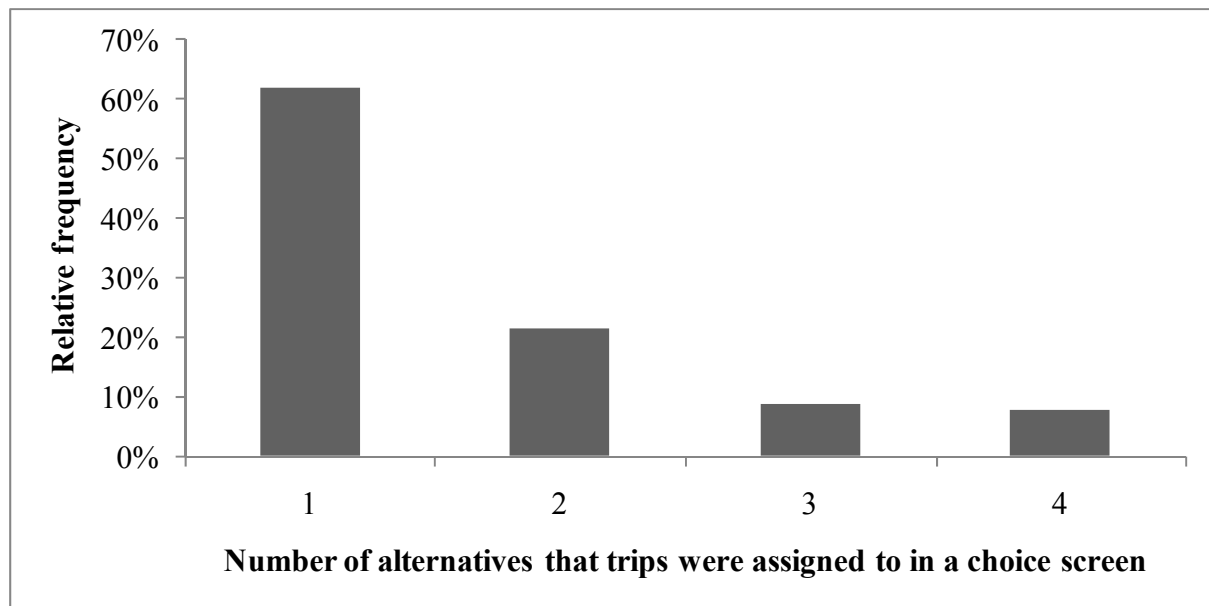


Figure 4.7: Assignment of trips to different alternatives in a choice screen

Knowing that a majority of respondents distribute the trips among more than one alternative, the question then becomes: how much dispersion is there? About 4% of the respondents distribute the trips in all 11 choice tasks in such a way that there is no obvious better alternative (e.g. no alternative gets assigned more than 4 trips). About 6.5% of the respondents adopt this distribution pattern in 6 or more of the 11 choice tasks. In 70% of all the choice tasks performed by respondents (1115*11 in total), one of the alternatives was assigned 8 or more trips. This increases to about 80% if we lower the criterion to 6 or more trips.

4.5 Conclusions

In this chapter, we investigated the characteristics of the respondents from the data collection presented in Chapter 3. The data were collected among car commuters that drive to work at least three times per week, experiencing congestion of at least 10 minutes during their commute. This screening of respondents implies that we do not have a representative sample of the Dutch population, or even of the Dutch workforce. This is not important in estimating choice models. For forecasting effects of road pricing, weights need to be applied to create a representative model of the effects of road pricing.

Compared to the Dutch population and to results from a study into drivers in congestion, our respondents have a slightly higher income, over represent the 25-55 age group, have a higher level of education, and include disproportionately more males than females. Males report higher household incomes than females, respondents with a higher level of education report higher income levels and respondents with a higher level of education tend to be younger than respondents with a lower level of education. These differences are likely to lead to higher value-of-time estimates in results from the choice models.

Regarding the departure and arrival time constraints of respondents, 73.2% report that they can depart from home when they want, but 54.7% of respondents state that they have to arrive at work within certain time limits. Arriving later than a specific time is the most reported constraint. In order to investigate how this influences choice behaviour, we will estimate

choice models (Section 5.3.2) that take into account extra scheduling delay components for travelling outside the acceptable bandwidths in departure and arrival times.

The average reported mean travel time of respondents is about 62 minutes. With the mean free-flow travel time being about 36 minutes, this results in an average reported delay of 26 minutes. This is substantial, but comparable to results from the drivers in the congestion study. We expect that respondents overestimate the travel time in congestion, possibly by including travel time unreliability. As a result of congestion and travel time unreliability, the respondents, on average, depart 26 minutes earlier than preferred, and, on average, they arrive 6 minutes later than preferred. These results show that respondents are more likely to change to earlier departure times than later arrival times, which is something we will also investigate in the next chapter by estimating different departure time choice models.

Besides the respondents' socio-demographic characteristics and the characteristics of their current trips, we also analysed how respondents distributed the 10 trips among 4 alternatives. Since distributing 10 trips is a choice task for a stated choice experiment which is not normally used, we need to know how respondents handled the task. We find that about 40% of the respondents always assign all 10 trips to a single alternative only. This means that a large group among the respondents assign their 10 trips over two or more alternatives, which is what we expected and was the reason for adopting a 10-trip distribution task rather than a single-trip choice task. On the other hand, about 4% of the respondents distribute the trips in all 11 choice tasks in such a way that there is no obvious better alternative. However, 80% of the respondents assigned 6 or more trips to one alternative, which means that respondents were able to identify a preferred alternative. The distribution of 10 trips results in more choices for alternatives with lower road pricing fees. The choice models estimated with these data will result in higher price sensitivities and/or lower sensitivities towards rescheduling, route and mode change.

5 Modelling behavioural responses to road pricing

In Chapter 1, we discussed the route, departure time choice, and mode behaviour of commuters. We found that for route choice, different time and cost components influence choice behaviour. For departure time choice, we found that there were several approaches with different explanatory attributes, and we adopted the scheduling approach. With regards to mode choice, there is extensive research on attributes of importance related to travel time, travel costs and the comfort attributes of different modes. Based on the analyses in Chapters 1 and 2, a survey was designed to collect data on the effect of different attribute values on choice behaviour. The subject of this chapter is to use those data and to model the choice behaviour of respondents using discrete choice models based on random utility theory (see Ben-Akiva and Lerman (1985)). The models in this chapter are not estimated on a single choice between alternatives but rather on frequencies or shares, as 10 trips were distributed. The choice models in this chapter focus on the specification of scheduling delay, travel time and travel cost components. In Chapter 6, the focus will then be on how travel time unreliability affects choice behaviour.

The purpose of this chapter is to identify the attributes that determine commuters' choice behaviour under changing travel conditions in terms of travel times and travel costs. Different utility functions are formulated and parameters are estimated to identify: 1) which attributes are of importance in departure time choice and 2) how sensitive commuters are towards these attributes.

In developing utility functions, several issues arise related to both the attributes and the resulting parameter estimates. Regarding the scheduling delay attributes in the utility function, an important issue is whether scheduling delay relates to arriving early or late, or to departing early or late. A second issue is whether commuters have a constant sensitivity towards these scheduling, cost and time attributes.

Finally, there are two issues related to travel time which are covered in this chapter. The first issue is again whether commuters are non-linear in their sensitivity towards travel time. The second issue is whether the sensitivity towards free-flow travel time under free flow conditions is different than towards travel time under congested conditions. Methodologically,

the issues are how to model the non-linear sensitivity of commuters and how to compare sensitivities between different time and cost components if the scales of the attributes are different.

In order to address all of the above issues and to meet the purpose of the chapter, a trial-and-error approach of MNL-model estimation was adopted. MNL models are robust and easy to estimate and interpret, but possess some methodological down-sides as well. The first issue is that we cannot treat the data from the stated choice experiment as panel data (repeated choices of the same individual), which affects both parameter estimates and their significance. The second issue is that we cannot include complex error-structures which may be important in, for example, departure time choice, where the time alternatives are ordered (8:00 a.m. is before 9:00 a.m.) and they are correlated (8:15 a.m. is a similar alternative to 8:20 a.m. but not to 11:30 a.m.). In the models presented in this chapter, we do not consider discrete time periods as alternatives, but we use the four alternatives that were presented in the stated choice experiment.

Different issues were addressed both separately and jointly in the choice models, as all parameter estimates may change when adding, removing or recoding an attribute in the utility function. The models were evaluated and compared based on the significance of attributes, the plausibility of parameter estimates and goodness-of-fit measures. The starting point in the approach is the estimation of a reference model containing travel time, travel cost and scheduling delay attributes in their simplest form. We will then use alternative utility function specifications to improve on the reference model

The main contribution of the chapter is the investigation of the scheduling of trips, looking both at the departure and arrival time side of a trip. It appears that both are important. We also investigated non-linear sensitivities toward rescheduling, amongst others, by including acceptability bandwidths for rescheduling. Since we are interested in the effects of road pricing on departure time choice behaviour, we also looked at the decomposition of cost terms and non-linearities towards transport costs.

Chapter outline

This setup of this chapter is as follows. In Section 5.1, we elaborate on the modelling approach used in this chapter. We then discuss the reference model in Section 5.2. In the succeeding sections we examine deviations from the reference model. In Section 5.3, alternative specifications of scheduling attributes are examined. In Section 5.4, we address alternative cost attributes, and in Section 5.5, the influence of different specifications of travel time attributes. This chapter ends with conclusions in Section 5.6.

5.1 Modelling approach

In this section, we present the modelling approach we adopted in order to model the choice behaviour based on the data from the stated choice experiment presented in Chapters 3 and 4. We use discrete choice modelling techniques, which are based on the random utility theory (see Ben-Akiva and Lerman (1985)), to model the choice behaviour. We use the most applied and simplest model form: the MultiNomial Logit (MNL) model. Using discrete choice models, we are able to calculate a probability that a specific choice alternative is chosen from a given, limited (hence discrete) set of options (hence multinomial). These discrete choice models are derived from the assumption that decision-makers exhibit utility maximising behaviour. This means that a decision-maker chooses an alternative from a set of alternatives

on the basis of the attributes of each of the alternatives. Each attribute of each choice alternative has a certain value (for example, a travel time of 30 minutes in alternative A), and a specific attribute with a specific value in a specific alternative may be valued more by decision makers, or less, than similar attributes in other choice alternatives with other values as well as other attributes in the same choice alternative. Using this approach, the preference for a certain choice alternative can be expressed in a mathematical form: the utility function. The utility that a decision-maker obtains from choice option i is decomposed into two parts: a systematic component of utility (V_{in}) and a random component of utility (ε_{in}).

$$U_{in} = V_{in} + \varepsilon_{in}$$

where,

$$U_{in} = \text{utility of choice alternative } i \text{ for decision-maker } n \quad (5.1)$$

$$V_{in} = \text{systematic component of utility}$$

$$\varepsilon_{in} = \text{random component of utility}$$

In most cases, the systematic component of utility consists of a linear-in-parameters function containing different attributes as is shown in Equation (5.2). This function may be expanded with an alternative specific constant or intercept.

$$V_{in} = \sum_k \beta_{ik} x_{ink}$$

where,

$$\beta_{ik} = \text{parameter for attribute } k \text{ for choice alternative } i \quad (5.2)$$

$$x_{ink} = \text{value of attribute } k \text{ for choice option } i \text{ and decision-maker } n$$

Note that the parameters in the utility function are not decision-maker dependent, but are average weights over all the decision-makers. In order to operationalise the model, assumptions are needed about the random component of the utility function. In most discrete choice model applications, it is assumed that the errors are independent (over choice options), identically (same distribution), type I extreme value distributed. This assumption results in the so-called MultiNomial Logit (MNL) model, which produces a closed form expression of the choice probability of choosing alternative i , see Equation (5.3).

$$P_{in} = \frac{e^{V_{in}}}{\sum_{j \in C_n} e^{V_{jn}}}$$

where,

$$P_{in} = \text{probability of decision-maker } n, \text{ choosing option } i \quad (5.3)$$

$$C_n = \text{choice set of decision-maker } n$$

When estimating a MNL model, we are looking for a set of parameter values (see Equation (5.2)) such that we maximize the likelihood of resembling the choices of all respondents in our data by the resulting model. In estimating MNL models, we thus need to specify utility functions for the alternatives between which decision-makers choose. In our case, we have four alternatives, and we can thus specify four utility functions. Three of the alternatives are car alternatives and we do not want to estimate different behavioural models for those

alternatives, or in other words, the attributes and their parameter estimates should be identical for the three car alternatives. In order to get unbiased parameter estimates, we include Alternative Specific Constants (ASC's) in the car utility function. This constant will 'pick up' all the other 'reasons', those not included as an attribute in the utility function, for why respondents are choosing a certain alternative. We are interested in finding the trade-offs between traffic conditions, both time and costs, and the rescheduling of trips from preferred timing conditions for choices between routes, modes and departure times. In investigating the trade-offs, different specifications of rescheduling, cost and time attributes in the utility function will be compared, but a generic utility function for alternative x in our data set is then given by Equation (5.4).

$$V_x = \underbrace{\beta_{0,x}}_{\text{ASC}} + \underbrace{\sum_k \beta_{c,x}^k c_x^k}_{\text{cost attributes}} + \underbrace{\sum_l \beta_{t,x}^l t_x^l}_{\text{travel time attributes}} + \underbrace{\sum_m \beta_{sd,x}^m sd_x^m}_{\text{scheduling delay attributes}}$$

where,

$$x \in \{A, B, C, D\}$$

β 's are the parameters we want to estimate

c, t, sd are the attributes for cost, travel time and scheduling delays

The MNL model is a model based on differences in attribute values between alternatives. We can therefore only specify $X-1$ ASCs, where X is the total number of alternatives. One of the ASCs needs to be assumed fixed, and in the models we present, we assume that the public transport ASC is fixed to zero.

The main modelling approach is to specify an estimable reference model from the generic utility function and then extend that model in different sections of this chapter. We compare different model specifications amongst each other and to this reference model. Table 5.1 shows where in this chapter these different specifications are investigated. In this chapter, we will look at the three components in our generic utility function separately, starting with the scheduling attributes, then the travel cost attributes and, finally, the travel time attributes. This is shown in the first column. For each of these components we investigate alternative attributes and attribute specifications, which are given in the second column. In order to identify each model, it is given a name which consist of letters that identifies the category of model (SD = Scheduling delays) and a number. In the last column, the section in which we present these models is given.

Table 5.1: Modelling outline: topics, naming and section references

Topic	Attribute specifications	Model naming	Section
Scheduling attributes	Departure and arrival time rescheduling	SDxx	5.3.1
	Acceptability bandwidths	ABxx	5.3.2
	Non-linear sensitivities	HPxx and PWLxx	5.3.3
Travel costs	Road pricing fee and fuel costs	RFxx	5.4
	Non-linear sensitivities	NLRFxx	
Travel time	Free-flow and congested travel time	TTxx	5.5
	Non-linear sensitivities	NLTTxx	

Different models will be presented in this chapter, but many more were estimated. We only present a very small subset here, in support of the research we want to explain. For the comparisons of different models, we will first assess the plausibility of individual parameter estimates, in combination with other parameters. We will then also look at the significance of parameter estimates. Lastly, we will look at the overall model fit by assessing changes in loglikelihood values. In order to improve the understanding of the behavioural meaning of different model results, we also construct an example commuter that we use to visualise how the disutility changes for different departure times in different models. Table 5.2 shows the departure and arrival time characteristics of this example commuter. The commuter has a preferred departure time of 8:00 a.m. and a preferred arrival time of 8:30 a.m., which results in a free-flow travel time of 30 minutes. The commuter can, within bandwidths, change his/her departure and arrival time. All bandwidth boundaries are 30 minutes earlier or later than the preferred departure and arrival time, except for the latest possible departure bandwidth, which is 15 minutes. The values for free-flow travel time, preferred departure and arrival time are close to the average responses in our sample (see Chapter 4).

Table 5.2: Example commuter characteristics

Commuter characteristic	Value
Earliest possible departure time	7:30 a.m.
Preferred departure time	8:00 a.m.
Latest possible departure time	8:15 a.m.
Earliest possible arrival time	8:00 a.m.
Preferred arrival time	8:30 a.m.
Latest possible arrival time	9:00 a.m.

Figure 5.1 shows the travel time and travel costs for this respondent for different departure times. These values are based more or less on the median reported traffic conditions by our respondents and a little bit higher than average road pricing fee than was shown in the stated choice experiment (3 euro compared to 2.67 euro). When looking at the scheduling of trips, we assume that there is no road pricing fee. The road pricing fees are used in the discussion of models focusing on different specifications of cost components in the utility function.

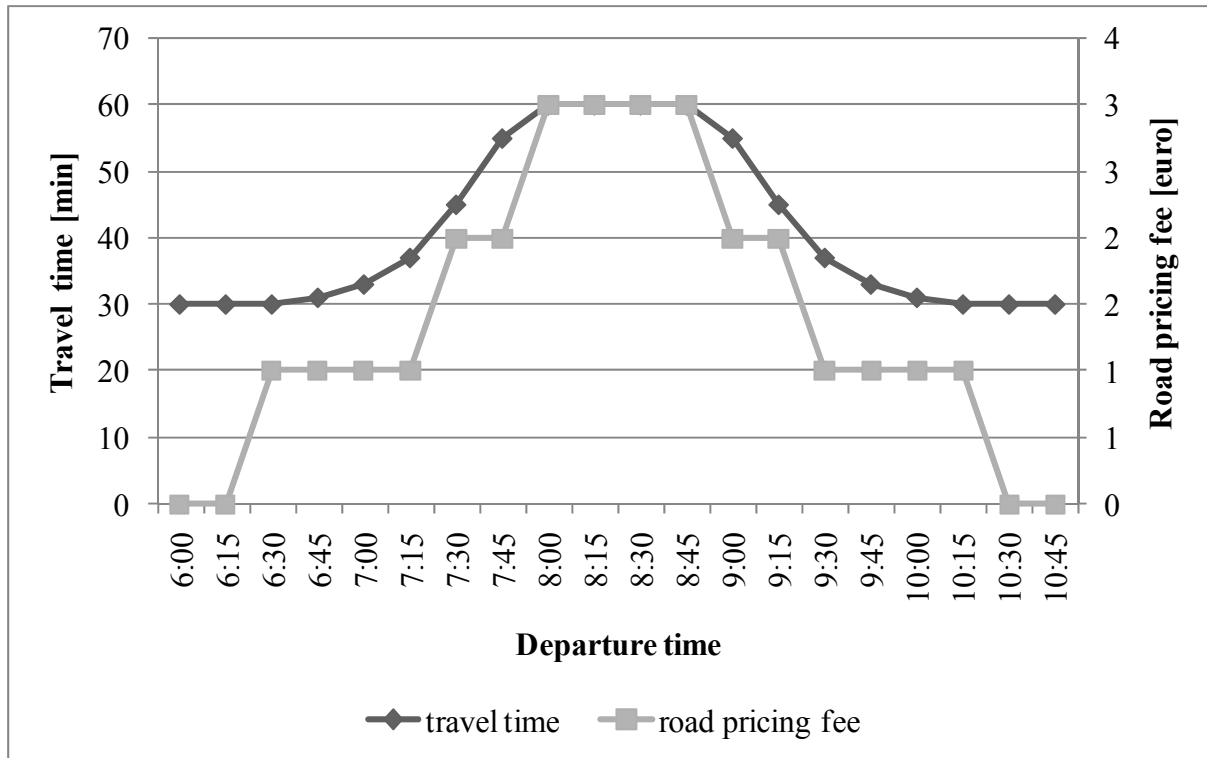


Figure 5.1: Travel characteristics for the example commuter

5.2 Reference departure time model

In this section, we present the utility functions for the reference model and the estimation results for this model. In the reference model, we only investigate linear sensitivities towards attributes for both car and public transport. As mentioned, the car alternatives should have generic attributes, except for alternative specific constants. The public transport alternative will have no ASC included. We also assume in the reference model that one total cost attribute describes the sensitivity towards costs and we assume that this attribute is generic over all alternatives. Travellers are thus equally sensitive to price, whether a euro is spent on a car trip or on a public transport trip. It also does not matter if a euro is spent on fuel or for paying a road pricing fee. With regards to travel time, we assume in the reference model that travellers are equally sensitive towards different travel time components. Furthermore, since we displayed travel time bandwidths to respondents in the car alternative rather than a single value, different specifications of this overall travel time attribute could be given. Here we will use the mean, or expected, travel time in the car alternatives. We expect that the sensitivity towards travelling by public transport is different from the sensitivity towards travelling by car and we thus estimate a parameter for each. We expect the same for the scheduling delay attributes in the reference model, and for both car and public transport, we start with arrival time scheduling delays as used by Hendrickson and Plank (1984), Small (1982). The resulting utility functions for each alternative are given by Equations (5.5) and (5.6).

$$V_{ix}^a = \beta_0^a + \beta_\theta \theta_{ix}^a + \beta_\tau^{\text{car}} \tau_{ix}^a + \beta_{asde}^{\text{car}} asde_{ix}^a + \beta_{asdl}^{\text{car}} asdl_{ix}^a \quad (5.5)$$

$$V_{ix}^{pt} = \beta_0^{pt} + \beta_\theta \theta_{ix}^{pt} + \beta_\tau^{pt} \tau_{ix}^{pt} + \beta_{asde}^{pt} asde_{ix}^{pt} + \beta_{asdl}^{pt} asdl_{ix}^{pt} \quad (5.6)$$

where,

i = respondent index

x = choice situation index

a = alternative index

V_{ix}^a = systematic utility of alternative a , where $a \in \{A, B, C\}$

β_0^a = alternative specific constants for car alternative a ,
relative to public transport

θ_{ix}^a = total travel costs for for car alternative a [euro]

τ_{ix}^a = expected travel time for car alternative a [min]

$asde_{ix}^a$ = arrival time scheduling delay early for car alternative a [min]

$asdl_{ix}^a$ = arrival time scheduling delay late for car alternative a [min]

$\beta_0, \beta_\tau^{\text{car}}, \beta_{asde}^{\text{car}}, \beta_{asdl}^{\text{car}}$ = parameters estimates for cost, travel time, asde and asdl

5.2.1 Calculating scheduling delays

The scheduling attributes in the utility functions presented in Equations (5.7)-(5.8) were not directly shown to respondents, but need to be calculated. Since, in these choice tasks, a bandwidth of work arrival times was presented rather than one specific time, it seems reasonable to base the calculation of scheduling delays for the car alternative on the expected arrival time, using the expected travel time. This and other approaches will be used in Chapter 6, when we investigate how to incorporate travel time unreliability into the departure time choice model. In this chapter, however, we use a simpler approach by identifying three alternative situations depending on the location of the preferred arrival time (PAT) relative to the arrival time bandwidth:

(1) PAT_i is later than the latest arrival time shown AAT_{ixa}^+ to respondents. In this case it is clear that $asdl_{ix} = 0$. The $asde_{ix}$ is calculated according to Equation (5.7) ;

$$asde_{ixa} = PAT_i - AAT_{ixa}^+ \quad (5.7)$$

(2) PAT_i is earlier than the earliest arrival time shown AAT_{ixa}^- to respondents. In this case, it is clear that $asde_{ix} = 0$. The $asdl_{ix}$ is calculated according to Equation (5.8);

$$asdl_{ixa} = AAT_{ixa}^- - PAT_i \quad (5.8)$$

(3) PAT_i is between the earliest arrival time AAT_{ixa}^- and latest arrival time AAT_{ixa}^+ . In this case, $asdl_{ixa}$ and $asde_{ixa}$ may both occur with different probabilities. In this chapter, we do not include these scheduling delays.

5.2.2 Reference model estimation results

The reference model parameter estimates are presented in Table 5.3. All parameters are significant and have expected signs. We would expect that the sensitivity towards scheduling delay early is lower than the sensitivity towards travel time, which we expect is lower than the sensitivity towards scheduling delay late. The estimation results show, however, that the

sensitivity toward scheduling delay early is almost equal to the travel time sensitivity, while the travel time sensitivity is twice that of scheduling delay late. Both results are not as expected, albeit that the deviation in scheduling delay late sensitivity is more surprising. This parameter value for arrival scheduling delay late is significant, but we expect that alternative, possible non-linear-in-parameter specifications of scheduling delays may resolve the unexpected result found here.

Table 5.3: Reference model estimation results

	Parameter	T-Value
ASC_A	0.414	4.12
ASC_B	0.548	5.33
ASC_C	1.026	10.18
Travel cost [euro]	-0.066	-11.29
Expected car travel time [min]	-0.029	-24.77
Arrival scheduling delay early [min]	-0.028	-14.91
Arrival scheduling delay late [min]	-0.014	-3.00
Travel time public transport [min]	-0.027	-20.61
Scheduling delay early public transport [min]	-0.020	-5.62
Scheduling delay late public transport [min]	-0.013	-3.73
Log(ASC)		-15713
LogL		-15267
Pseudo Rho2		0.028

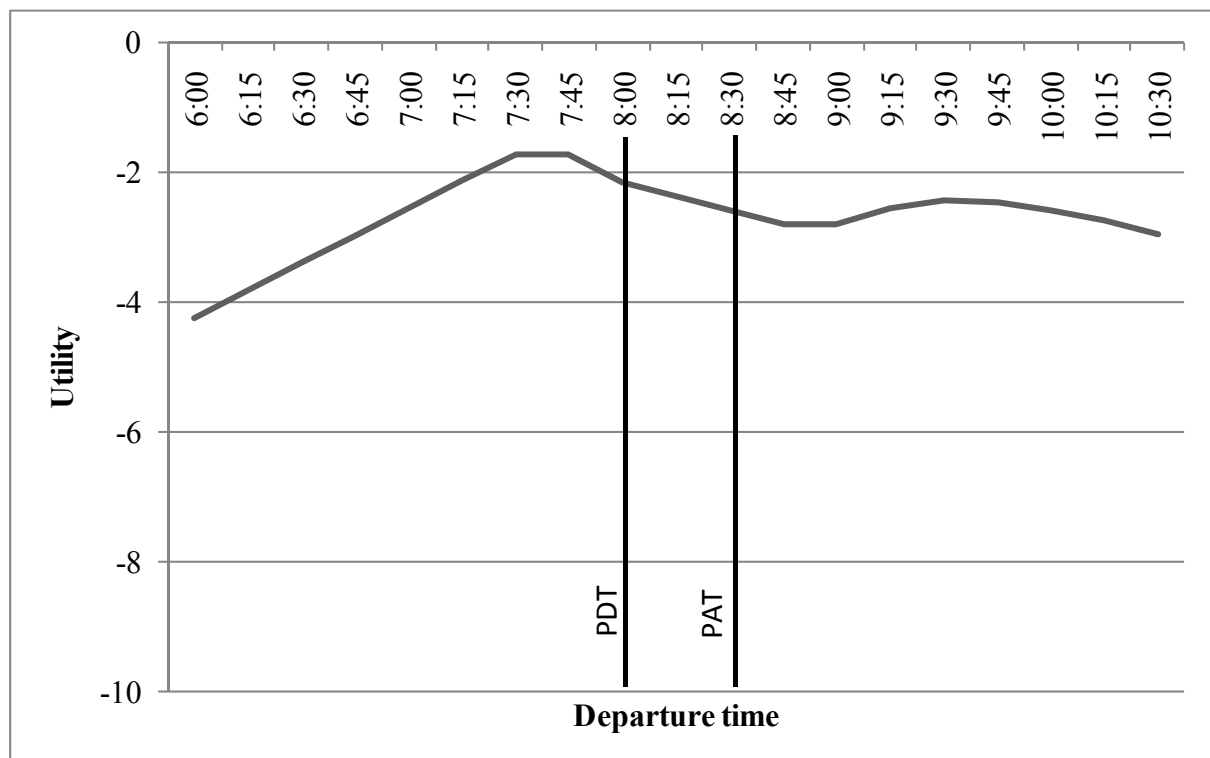
The estimation results also show strong positive and significant alternative specific constants (ASC_A-C). This implies that, all else being equal, respondents are more likely to assign trips to the car alternatives and that they are more likely to assign trips to alternative C than to alternatives B and A. The significant estimates for the ASC's are not surprising, although we would have expected that the size of the ASC's for the alternatives A, B and C would be similar. There is something attractive about alternative C that we are not explaining by any of the attributes included in the current utility function. In other models in this chapter, we will attempt to identify this attractiveness of alternative C in a behavioural explainable attribute, which may be non-linear sensitivity to the road pricing fee.

Table 5.4 presents the willingness-to-pay (WTP) estimates that can be derived from the parameter estimates. The resulting values-of-time (VoT) are not unreasonable, albeit they are higher than we would expect. As discussed in Section 5.2, higher than national average values of time are to be expected given the socio-demographic characteristics of our respondents. The VoT, VoASDE and VoASDL for public transport are lower than for car, which is as expected, but we expected these differences to be larger. Since WTP estimates are the quotient of two parameter estimates they are likely to be affected changes in specifications of the utility. As we will include other attributes and non-linear in parameter specifications of utility function we expect to find other WTP estimates, hopefully with values closer to those found in other studies in the Netherlands.

Table 5.4: WTP components derived from the reference model

WTP component	Value [euro/h]
VoT car	26.87
VoASDE car	25.63
VoASDL car	12.74
VoT public transport	25.03
VoASDE public transport	18.57
VoASDL public transport	11.79

In Figure 5.2, we used the reference model to calculate the utility of different departure times for the example respondent. The resulting utility profile is clearly not linear. The utility is highest at 7:30 a.m. – 7:45 a.m., which would be the best time for our commuter to depart. Departing earlier than 7:30 a.m. leads to additional disutility because the arrival scheduling delay early increases, while the travel time remains constant. After 7:30 a.m., there is an increase in travel time, which causes lower utilities. Later, the travel times decrease, while the scheduling delay late attributes cause additional disutility.

**Figure 5.2: Travel utility for the example commuter at different departure times**

The estimation results of the reference model show that further investigation into modelling rescheduling is needed, since the current results are somewhat counterintuitive. Non-linear sensitivities are possibly the cause of this, but different specifications of scheduling components may resolve this issue as well. It also seems that the values-of-time resulting from the model are high, and we are interested to see how stable these estimates are with different model specifications before drawing conclusions.

5.3 Scheduling components

In this section, we investigate whether alternative specifications of scheduling components in the utility function might improve model performance and lead to more intuitive ratios of sensitivities towards rescheduling and travel time. We will proceed in three different ways, which are presented in three different subsections. First (subsection 5.3.1), we will look at departure time rescheduling in comparison to arrival time rescheduling, and we investigate the combination of both rescheduling specifications as well. We then, in subsection 5.3.2, look at rescheduling outside the acceptable bandwidths reported by respondents and add additional attributes for this to the utility function. Finally, in subsection 5.3.3, we look at non-linear sensitivities towards rescheduling.

5.3.1 Arrival time and departure time scheduling

In the reference model, we addressed the scheduling delays only as deviations from the preferred arrival time of a trip. As shown in Figure 1.5, however, it is also possible that departure time scheduling delays exist instead or together with arrival time scheduling delays. Departure time scheduling delays can be derived by using the actual and preferred departure times as given by Equations (5.9) and (5.10).

$$dsde_{ixa} = \max\{PDT_i - ADT_{ixa}, 0\} \quad (5.9)$$

$$dsdl_{ixa} = \max\{ADT_{ixa} - PDT_i, 0\} \quad (5.10)$$

where,

ADT_{ixa} = actual departure time, for alternative $a \in \{A, B, C\}$

PDT_i = preferred departure time

In the reference model, two arrival time scheduling delay parameter were estimated. We can now add two departure time scheduling delay parameters (model SD01), we can replace the arrival time scheduling delay attributes (model SD02) or we can create other combinations of departure and arrival time scheduling delays (model SD03). In the third model, we remove the attributes with insignificant parameters in model SD01 from the utility function. The estimation results for these models are presented in Table 5.6.

Table 5.5: Different models with arrival time and departure time rescheduling

Model name	Description
SD01	Reference model plus departure time scheduling delay early and late
SD02	Reference model arrival time replaced by departure time scheduling early and late
SD03	Model SD01 without insignificant parameters – dsde and asdl were removed

When we add departure time scheduling attributes to the reference model (= model SD01), we see that the dsdl and asde are significant and the other two are not significant. Furthermore, we see that the sensitivity towards departing later (dsdl) in model SD01 is much larger than the sensitivity towards arriving late (asdl) in the reference model. So the two attributes do not seem interchangeable. The high sensitivity towards dsdl is consistent in models SD02 and SD03. In model SD02, we completely replaced the arrival time scheduling delays with departure time scheduling delays. The dsde parameter is significant, but much lower than the asde parameter in the reference model. This suggests that departure and arrival time rescheduling is felt differently. However, the sensitivity towards travel time and total costs

also change in model SD02, which results in a lower VoT. The change in sensitivity towards travel time is probably caused by the travel time bandwidths, which are included in the calculations of both the *expected* travel time and the *expected* arrival time scheduling delays. The overall model fit is somewhat improved by adding departure time rescheduling in model SD01 and SD03. For model SD02, with only departure time rescheduling, the model fit deteriorates somewhat compared to the reference model.

Table 5.6: Models with departure time and arrival time scheduling delays

	Reference		SD01		SD02		SD03	
	Para-meter	T-Value	Para-meter	T-Value	Para-meter	T-Value	Para-meter	T-Value
ASC_A	0.414	4.12	0.419	4.18	0.364	3.65	0.415	4.16
ASC_B	0.548	5.33	0.497	4.77	0.366	3.64	0.504	4.98
ASC_C	1.026	10.18	1.002	9.91	0.962	9.56	1.013	10.08
Total travel cost	-0.066	-11.29	-0.066	-11.05	-0.077	-13.05	-0.069	-11.73
Car travel time	-0.029	-24.77	-0.032	-20.17	-0.024	-18.85	-0.030	-25.28
DSDE			0.002	1.34	-0.009	-10.25		
DSDL			-0.087	-5.84	-0.095	-6.80	-0.088	-6.39
ASDEcar	-0.028	-14.91	-0.030	-11.35			-0.027	-15.00
ASDLcar	-0.014	-3.00	0.002	0.28				
PT travel time	-0.027	-20.61	-0.029	-20.72	-0.026	-19.56	-0.028	-21.03
ASDEpt	-0.020	-5.62	-0.021	-5.90	-0.021	-5.69	-0.021	-5.89
ASDLpt	-0.013	-3.73	-0.014	-3.97	-0.014	-3.94	-0.014	-3.97
Log(ASC)		-15713		-15713		-15713		-15713
LogL		-15267		-15249		-15320		-15251
Pseudo Rho2		0		0		0		0
VoT car		27		29		19		27
VoDSDE car				N.S.		7		
VoDSDL car				78		74		77
VoASDE car		26		27				24
VoASDL car		13		N.S.				
VoT PT		25		26		20		25
VoASDE PT		19		19		16		19
VoASDL PT		12		12		11		12

The reference model estimates showed higher sensitivities to both scheduling delay early and late than travel time. This is not in line with findings by others, and is possibly even counterintuitive for commuter trips. In all three models (SD01 – SD03), the relative importance of scheduling delay early and late is now better in line with our expectation that commuters are most sensitive to scheduling delay late, then travel time and least sensitive towards scheduling delay early.

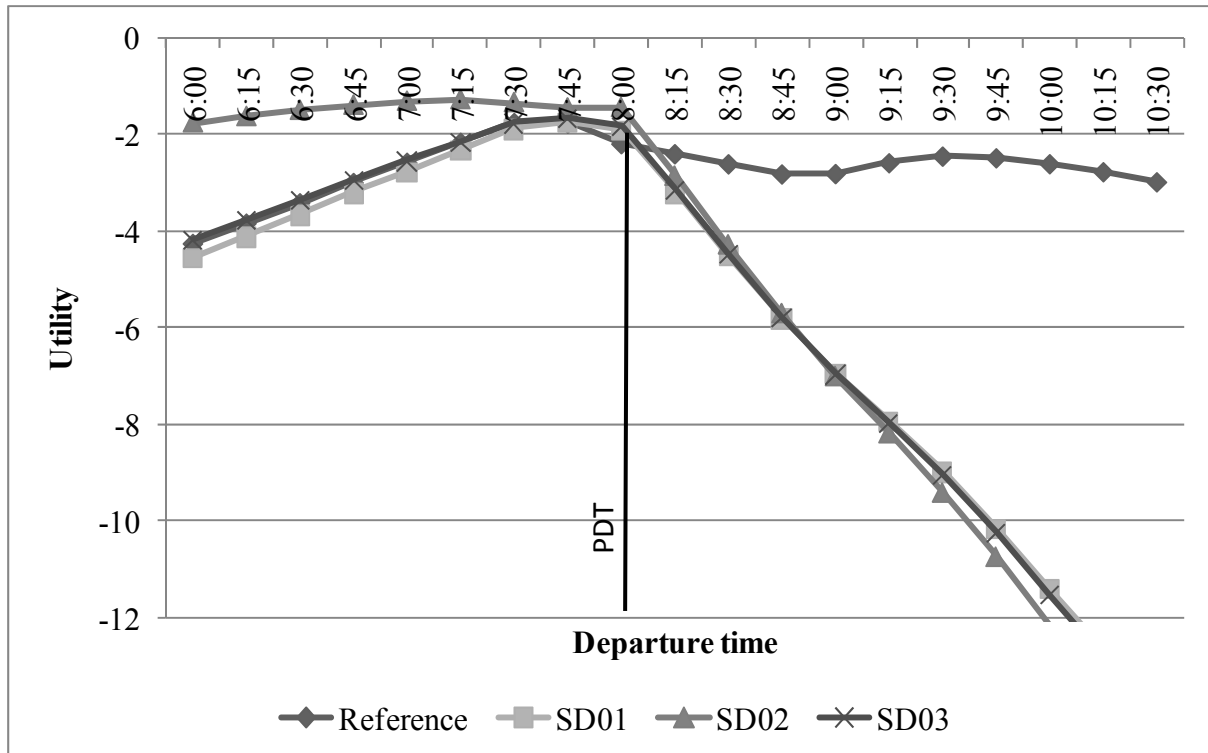


Figure 5.3: Utility for example respondent for different scheduling models

Although the model estimates in the models SD01 through SD03 are more in line with our expectations, we are still interested in further improvements. For example, the insignificance of departure time scheduling delay early is somewhat surprising and we expect such a parameter to be significant for at least large rescheduling. We examine this non-linear sensitivity later in this chapter, as we will first look at the rescheduling outside of the reported acceptable bandwidths for departing and arriving.

5.3.2 Departure and arrival time constraints

In the reference model and in the models presented in the previous subsection (SD01-SD03), we assumed linear sensitivities towards departure and arriving earlier or later. In all the model estimates so far, we have seen that there is reason to believe that non-linear sensitivities may exist. In this section, we explore this by using additional attributes for rescheduling outside acceptable departure and arrival time bandwidths. As shown in Section 4.2.5, about 65% of the respondents have arrival time constraints, while only 27% have departure time constraints. For departure time, there is an even split between having an early and/or late departure constraint, while for arrival time, the arriving late constraint appears much more common. In Figure 5.4, we visualise how a commuter can reschedule from a preferred departure (PDT) and arrival time (PAT) by having an actual departure time (ADT) and an expected actual arrival time (E(AAT)). To this, we now add earliest (E) and latest (L) departure (D) and arrival (A) times (EDT, LDT, EAT and LAT).

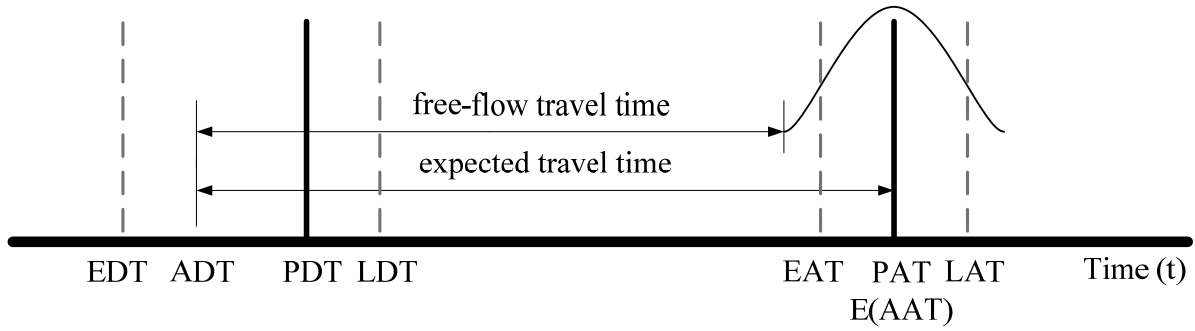


Figure 5.4: Departure and arrival time constraints around the preferred departure and arrival times

In this section, we added these various individual time constraints to the utility function to investigate whether departing or arriving outside the acceptable windows leads to additional disutility, resulting in a non-linear sensitivity towards scheduling delays. Four constraints, as shown in Figure 5.4, can be added to the utility function: departing earlier than acceptable, departing later than acceptable, arriving earlier than acceptable and arriving later than acceptable. These attributes were calculated according to Equations (5.11)-(5.14).

$$dte_{ixa} = \max \{ EDT_i - ADT_{ixa}, 0 \} \quad (5.11)$$

$$dtl_{ixa} = \max \{ ADT_{ixa} - LDT_i, 0 \} \quad (5.12)$$

$$ate_{ixa} = \max \{ EAT_i - AAT_{ixa}^+, 0 \} \quad (5.13)$$

$$atl_{ixa} = \max \{ AAT_{ixa}^- - LAT_i, 0 \} \quad (5.14)$$

where,

i = index for respondent

x = index for choice task

a = index for alternative, $a \in \{A, B, C\}$

dte_{ixa} = departing earlier than acceptable [min]

dtl_{ixa} = departing later than acceptable [min]

ate_{ixa} = arriving earlier than acceptable [min]

atl_{ixa} = arriving later than acceptable [min]

EDT_i = earliest possible departure time

LDT_i = latest possible departure time

EAT_i = earliest possible arrival time

LDT_i = latest possible arrival time

Besides defining these parameters as attributes in minutes too early or late, we also used dummy specifications where a dummy has a value of 1 for situations where rescheduling outside the acceptability bandwidth occurs. These dummies are named $ddte_{ixa}$, $ddtl_{ixa}$, $date_{ixa}$ and $datl_{ixa}$. In Table 5.7, we present descriptions of the different models that are discussed in this section. These models vary in dimensions. In the first dimension, the model which serves as a base is varied and is either the reference model or the SD03 model from the previous section, which includes departure and arrival time scheduling components.

The second and third dimension set which attributes are used for too early and too late scheduling.

Table 5.7: Description of models estimated with rescheduling outside acceptable bandwidth

Model name	Base model	Too early and late parameters in minutes	Too early and late parameters as dummy's
AB01	Reference	dte, dtl ,ate, atl	
AB02	SD03	dte, dtl ,ate, atl	
AB03	Reference	dte, dtl ,ate, atl	ddte,ddtl,date,datl
AB04	SD03	dte, dtl ,ate, atl	ddte,ddtl,date,datl
AB05	SD03	dte, dtl	datl

As Table 5.7 shows, models are included only with too early and too late attributes specified in minutes and with combinations of specification in minutes and dummy's. Dummy only models were estimated as well, but performed less. The AB05 model is a model based on AB04, from which all insignificant parameters were removed. Table 5.8 shows the estimation results for the different models. In the table, the departure and arrival time scheduling parameter estimates are presented in separate blocks to make comparisons easier.

Table 5.8: Model estimation results with departure and arrival time constraints

	Ref		AB01		AB02		AB03		AB04		AB05	
Variable	Par	T-val	Par	T-val	Par	T-val	Par	T-val	Par	T-val	Par	T-val
ASC A	0.414	4.12	0.442	4.39	0.444	4.43	0.437	4.34	0.444	4.43	0.453	4.52
ASC B	0.548	5.33	0.587	5.69	0.544	5.35	0.585	5.65	0.558	5.48	0.566	5.56
ASC C	1.026	10.18	1.067	10.54	1.055	10.45	1.064	10.49	1.056	10.44	1.063	10.53
Total cost	-0.066	-11.29	-0.066	-11.31	-0.069	-11.74	-0.066	-11.36	-0.069	-11.77	-0.069	-11.75
TT car	-0.029	-24.77	-0.029	-24.59	-0.030	-25.10	-0.029	-24.68	-0.030	-25.18	-0.030	-25.14
dte			-0.017	-9.47	-0.017	-9.50	-0.018	-8.03	-0.018	-7.97	-0.017	-9.48
ddte							0.066	0.78	0.049	0.57		
dsde					-0.088	-6.39			-0.084	-6.02	-0.083	-5.99
dtl			-0.014	-2.44	-0.013	-2.34	-0.018	-2.37	-0.019	-2.47	-0.012	-2.10
ddtl							0.162	1.11	0.207	1.41		
asde	-0.028	-14.91	-0.027	-14.09	-0.026	-14.11	-0.027	-13.93	-0.026	-14.17	-0.026	-14.39
ate			0.006	0.99	0.006	1.03	0.014	1.89	0.014	1.92		
date							-0.280	-1.75	-0.284	-1.77		
asdl	-0.014	-3.00	-0.014	-2.95			-0.009	-1.92				
atl			-0.013	-2.25	-0.014	-2.38	0.008	1.10	0.008	1.03		
datl							-0.632	-4.71	-0.617	-4.66	-0.533	-5.08
TT PT	-0.027	-20.61	-0.027	-20.43	-0.028	-20.85	-0.027	-20.49	-0.028	-20.90	-0.028	-20.85
asde PT	-0.020	-5.62	-0.021	-5.69	-0.022	-5.96	-0.021	-5.70	-0.022	-5.94	-0.022	-5.94
asdl PT	-0.013	-3.73	-0.013	-3.87	-0.014	-4.12	-0.013	-3.87	-0.014	-4.10	-0.014	-4.10
LogASC		-15713		-15713		-15713		-15713		-15713		-15713
Log L		-15267.2		-15215.6		-15201.3		-15184.5		-15198.8		-15188.3
P-Rho2		0.028		0.032		0.033		0.034		0.033		0.033
VoT car		26.87		26.60		26.60		26.41		26.39		26.41

The estimation results show that the parameters for departure time rescheduling outside the acceptable bandwidth are significant in all models. For arrival time rescheduling outside the acceptable bandwidth, only the late parameters are significant and the dummy variable performs better than the minute specification.

In the previous section, we saw that departure time scheduling delay early parameters were insignificant, but as we expected, there is a limit to how much respondents are willing to reschedule to earlier departures. The sensitivity towards early departure scheduling outside the acceptable bandwidth is about half the sensitivity towards travel time. For late departure time scheduling outside the acceptable bandwidth, the sensitivity is slightly lower than for early departure scheduling outside the acceptable bandwidth, but this parameter is significant together with departure scheduling delay late.

On the arrival rescheduling side, it seems that arrival time scheduling late is no longer significant after introducing departure time rescheduling in the previous section. Even before introduction, the sensitivity towards arrival time scheduling late was counterintuitive. When introducing arrival time rescheduling late outside the acceptable bandwidth, either the minute or dummy specification are significant and the dummy specification results in a better model fit (about 10 loglikelihood points when comparing model AB02 and AB05). The overall loglikelihood of model AB05 improves by approximately 63 loglikelihood points by adding 3 parameters.

Figure 5.5 shows how the travel utility differs for the example commuter using different models. The grouping between models based on the reference and based on model SD03 can easily be distinguished. The most notable difference between the different models is that for later departures (after about 7:45), the utility decreases rapidly. This decline had already occurred after the introduction of the departure time rescheduling, but including outside bandwidth rescheduling has furthered this. The differences in utilities between models are smaller of earlier departures (6:00-7:00) than for later departure times (7:00-8:00). For model AB05, the highest utility no longer occurs at 7:00 but at 7:15.

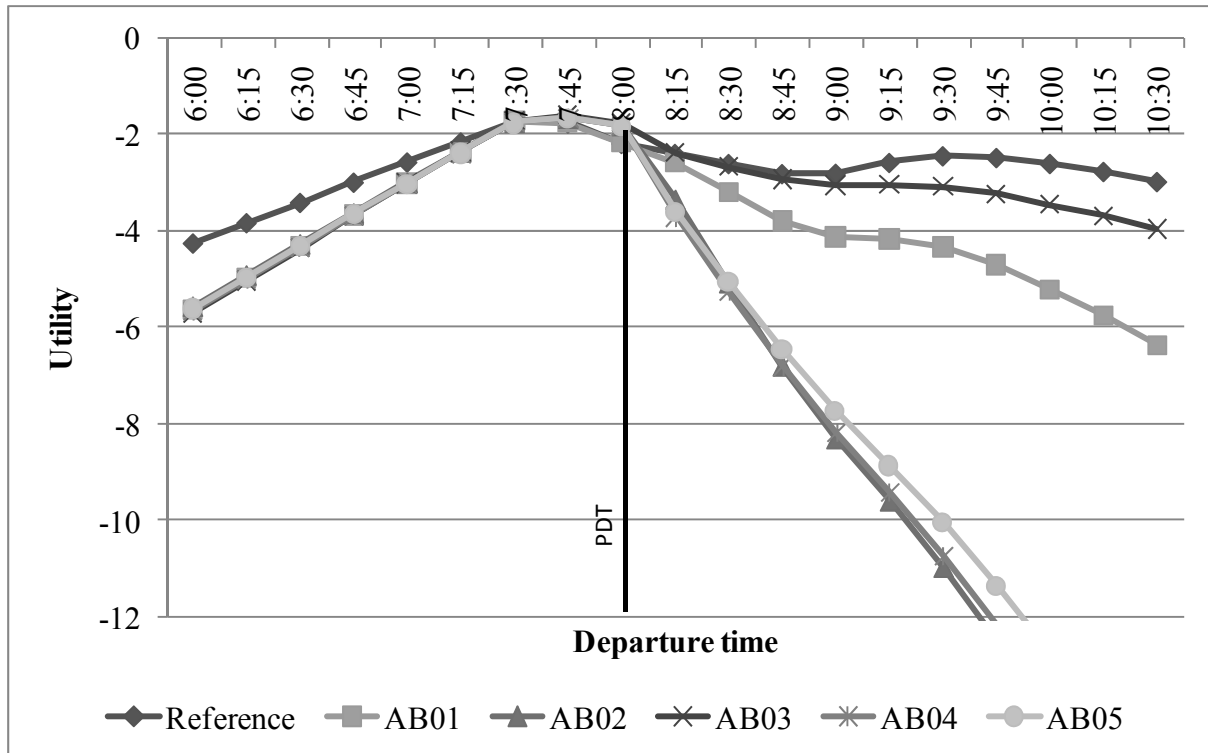


Figure 5.5: Travel utility for example respondent with acceptability bandwidth models

To summarize, we see that adding rescheduling outside the acceptable bandwidth reported by our respondents improves the model fit, and particularly, the rescheduling outside the departure time bandwidth is found to be important. The number of respondents that report arrival time bandwidths, however, is higher than respondents faced with departure time bandwidths (see Table 4.3). For rescheduling outside the arrival time bandwidth, it seems that a dummy for too late arrival performs better than a minute specification. A penalty thus exists for arriving too late that is independent from the amount of lateness. In this section, we found evidence of non-linear sensitivities towards rescheduling for respondents with some acceptable bandwidths of departure and arrival times. In the next section, we further explore the non-linear sensitivity regardless of the existence of such bandwidths.

5.3.3 Non-linear sensitivity towards rescheduling

Since we expect, and already have found, non-linear sensitivities towards rescheduling, we will further explore this in this section using two different viewpoints. The first viewpoint considers that as the deviations from the preferred time of travel get larger, the disutility of rescheduling should grow at a faster rate, quickly generating almost infinite disutility for departure periods outside a feasible region. The second viewpoint assumes that at some point the exact amount of rescheduling does not matter anymore, large is large, so that the disutility approaches some asymptotic value as the scheduling delay values become large. In this section, we consider both points of view, and a large variety of models were estimated, starting from the reference model. The first model (HP01) is inspired by Hendrickson and Plank (1984), and linear and quadratic terms for arrival time rescheduling are included. In model HP02, the linear and quadratic terms for departure time rescheduling were added to the utility function. In the last model (HP03), results from different models in which the non-linear terms for departure and arrival time rescheduling were combined with non-linear terms for scheduling outside the acceptable bandwidths from the previous section.

Table 5.9: Description of models with non-linear specifications of scheduling delays

Model name	Base model	Non-linear attributes
HP01	Reference	Quadratic arrival time scheduling
HP02	Reference	Quadratic departure and arrival time scheduling
HP03	AB05/HP02	Quadratic terms for all scheduling attributes

The estimation results for all the different models are presented in Table 5.10. In model HP01, the quadratic terms for arrival time rescheduling were added to the reference. Only for *asdl* is the quadratic term significant, but the resulting parameter estimate is positive. This leads to positive utility when arrival time scheduling delay late values are above 11 minutes. This is counterintuitive. In model HP02, departure time rescheduling attributes (both linear and quadratic) were added to model HP01 and the estimation results show that the quadratic terms for *dsde* and *asde* are significant. The *dsde*² parameter estimate is negative, while the *dsde* is positive, implying that with *dsde* values lower than 125 minutes, the net utility for departing early is positive. This is, again, counterintuitive. The *asde*² parameter is positive, while the *asde* parameter is negative. In this case, the net utility for arriving early is negative for scheduling early values under 115 minutes, which is well outside the range for which the model was estimated (and can be applied). In model HP03, the rescheduling outside of acceptable bandwidths was then included. The quadratic specification of departing too early was found significant and has a positive value. Together with the negative linear term for *dte*, a net negative utility results below *dte* values of 250 minutes. We find that there is a decreasing marginal disutility for increasing values of too early departure (*dte*), while at the same time there is a growing marginal disutility for increasing values of departing earlier (*dsde*). The similar growing marginal disutility of extra rescheduling is also found for late departure. In model HP02, we find some evidence of diminishing extra disutility with increasing *asde*, but when including scheduling outside of acceptable bandwidths, this no longer is the case. Except for the arriving too late dummy, no non-linear sensitivities towards arrival time rescheduling are included.

Table 5.10: Estimation results for non-linear scheduling models

	Reference		HP01		HP02		HP03	
	Par	T-value	Par	T-value	Par	T-value	Par	T-value
ASC_A	0.414	4.13	0.453	4.50	0.378	3.71	0.413	4.10
ASC_B	0.548	5.33	0.524	5.06	0.333	2.95	0.466	4.36
ASC_C	1.026	10.18	1.039	10.25	0.848	7.60	0.938	8.60
Total cost	-0.066	-11.29	-0.065	-11.24	-0.070	-11.17	-0.070	-11.30
eTT car	-0.029	-24.77	-0.030	-24.90	-0.032	-19.78	-0.031	-20.71
dsde					0.011	3.91	0.008	3.54
dsde ²					-8.8E-05	-3.49	-6.8E-05	-2.91
dte							-0.030	-9.54
dte ²							1.2E-04	5.09
dsdl					0.025	0.36		
dsdl ²					-0.019	-1.38	-0.015	-5.03
dtl							-0.010	-1.83
dtl ²								
asde	-0.028	-14.91	-0.034	-7.60	-0.040	-7.62	-0.029	-11.13
asde ²			2.3E-04	1.62	3.5E-04	2.33		
asdl	-0.014	-3.00	-0.088	-4.71	-0.027	-1.16		
asdl ²			0.008	4.07	0.004	1.61		
atl dummy							-0.494	-4.66
TT PT	-0.027	-20.61	-0.028	-20.71	-0.029	-20.71	-0.028	-20.52
asde PT	-0.020	-5.62	-0.020	-5.58	-0.021	-5.83	-0.022	-5.93
asdl PT	-0.013	-3.73	-0.013	-3.68	-0.013	-3.87	-0.014	-4.03
Log(ASC)		-15713		-15713		-15713		-15713
LogL		-15267		-15258		-15240		-15170
Pseudo Rho2		0.028		0.029		0.030		0.035
VoT car		26.87		27.26		27.41		26.24

In Figure 5.6, the travel utility for the example respondent is presented for the different models that we presented with non-linear sensitivities towards scheduling attributes. The figure also contains the reference model and AB05 model utilities for comparative purposes. Model HP03 is the only model that really makes behavioural sense, in that utility profiles in Figure 5.6 do not become flat or even positive. The very steep descent of disutility for late reschedules is remarkable, but may not be impossible.

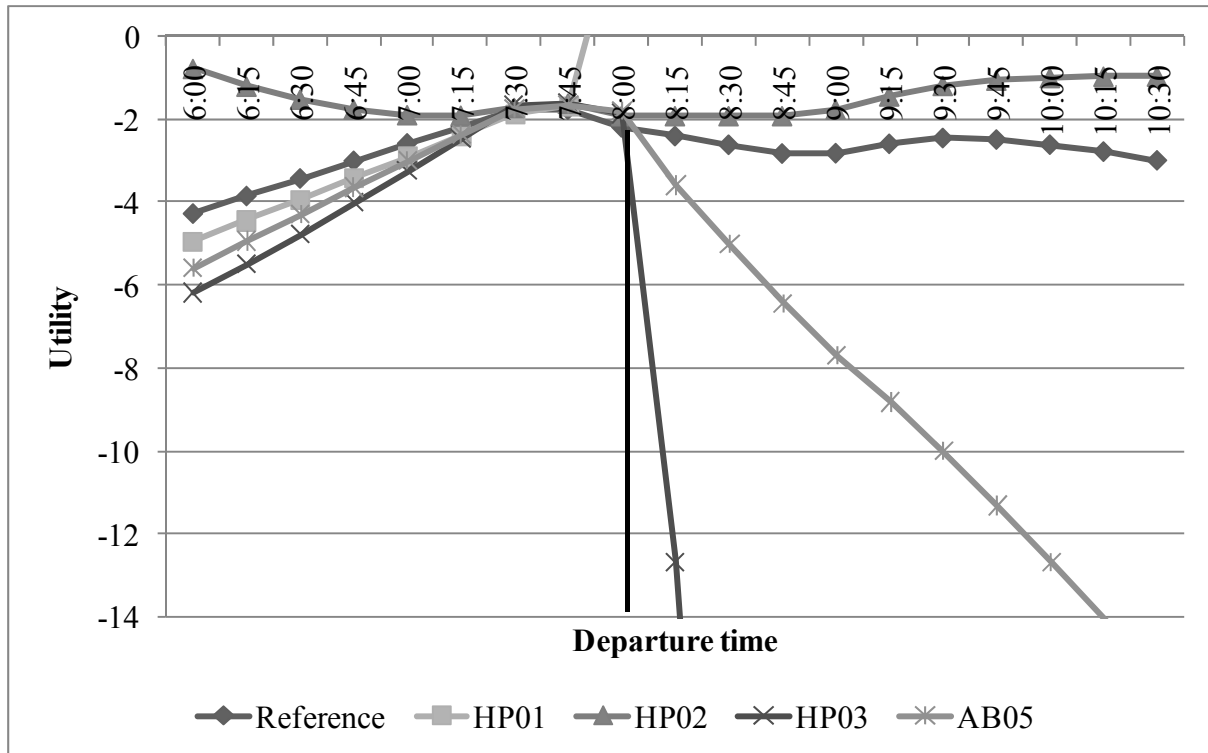


Figure 5.6: Utility for example travellers for different non-linear scheduling models

5.4 Road pricing fee and travel costs

So far, we have looked at different specifications of scheduling delay components in the utility function of a departure time choice model. We found non-linear sensitivities towards rescheduling for both departure and arrival time rescheduling components in the utility function. Also, including rescheduling outside acceptable bandwidths provides further explanation of the choice behaviour of the respondents in our data. Since behavioural responses towards road pricing are of central importance in this thesis, we will investigate the sensitivity towards road pricing fees more closely in this section. The objective is to determine whether different cost components (fuel and charge) have different sensitivities and if commuters have non-linear sensitivities towards cost components. If these differences and non-linear sensitivities towards different cost component exist, this is important to take into account when forecasting the effects of road pricing measures. Both issues are discussed sequentially in this section.

In the models we have presented so far, it was assumed that commuters are equally sensitive to different cost components. In other words, commuters are evenly sensitive to spending a euro on fuel, on a road pricing fee or on a public transportation ticket. This equal valuation of money is a viewpoint often adopted by economists, but it may not hold true in the travel decisions made by commuters. In analysing the sensitivity towards different cost components, it is important to distinguish between respondents who are compensated by their employers and those who are not. For the respondents who are compensated by their employer, the fuel costs and public transport costs are zero in the stated choice experiment, as was presented in Chapter 3.

In addressing the sensitivities of different cost components and potential non-linear sensitivities, we can either start from the reference model, or we may include the findings

about the sensitivities towards scheduling of trips as well. Both were conducted, but here we present models based on the HP03 model from the previous section, which contains non-linear scheduling attributes, departure and arrival time scheduling attributes and scheduling outside the acceptable bandwidth attributes. In the first model (RF01), we estimate a separate cost parameter for car and public transport. We then further separate the car costs into charge and fuel costs in model RF02. To model RF02, we then add a charge dummy to see if the imposing a charge in itself, regardless of the height, incurs disutility on travellers. Also, one of the charge levels in alternative C is zero, and including a dummy might reduce the differences in ASCs of the car alternatives. We first discuss the results of these three models before presenting models with non-linear sensitivities to cost attributes.

Table 5.11: Description of models with non-linear specifications of scheduling delays

Model name	Base model	Cost attributes
RF01	HP03	Separate total cost attribute for car and public transport
RF02		Separate charge and fuel cost parameters
RF03	RF02	Including a charge exists dummy

Table 5.12 shows the estimation results for the different cost attribute models. In model RF01, it becomes apparent that the sensitivity towards car costs is substantially higher than towards public transport costs. This also results in much higher VoT estimates for public transport than for car, where normally the reverse is found. There is also an apparent difference between sensitivities towards car costs for respondents that are currently compensated by employers and those who are not. In model RF02, the car costs are split up in fuel and road pricing charges. Since the fuel costs are zero for respondents currently receiving compensation from employers, we cannot estimate a fuel cost parameter for this group. Looking at the estimation results of model RF02, we see that non-compensated respondents are more than twice as sensitive to road pricing charges as those who are compensated. This implies that the compensated respondents may expect to receive compensation for the road pricing charges, thus being less sensitive to costs. Model RF02 also shows that non-compensated respondents are more sensitive to road pricing charges than they are towards fuel costs. This is a result we would expect to find, although the difference in sensitivities may diminish over time, after the implementation of road pricing. The extent of the difference may also depend on other design dimensions of the road pricing measure, as we discussed in Chapter 2. In model RF03, we attempt to distinguish between the sensitivity towards the height of the road pricing charges and the fact that road pricing charges exist by including a dummy for the existence of charges. The dummy parameter is negative and significant, and as we expected, including it reduces the sensitivity towards charges for both compensated and non-compensated respondents.

By estimating separate parameters for different cost components for car and public transport and within the car mode, we expected to also reduce some the unexplained difference in preference for alternative C that results from the higher ASC. The difference has reduced (about 20%), but not as much as we would have liked.

Table 5.12: Estimation results for models with varying cost attributes

	HP03		RF01		RF02		RF03	
	Par	T-value	Par	T-value	Par	T-value	Par	T-value
ASC_A	0.413	4.10	0.494	4.87	0.569	5.51	0.678	5.93
ASC_B	0.466	4.36	0.504	4.71	0.593	5.42	0.708	5.85
ASC_C	0.938	8.06	0.963	8.83	1.080	9.55	1.171	9.73
Total cost	-0.07	-11.3						
total cost emp. Comp			-0.087	-13.00				
total cost no comp			-0.159	-10.53				
fuel cost no comp					-0.166	-8.63	-0.166	-8.62
chargecomp					-0.077	-11.03	-0.075	-10.65
charge no comp.					-0.191	-10.78	-0.188	-10.64
charge dummy							-0.099	-2.22
eTT car	-0.031	-20.71	-0.032	-21.09	-0.031	-21.02	-0.032	-21.11
dsde	0.008	3.54	0.008	3.86	0.008	3.82	0.008	3.84
dsde ²	-6.8E-05	-2.91	-8.7E-05	-3.66	-8.1E-05	-3.38	-7.8E-05	-3.25
dte	-0.03	-9.54	-0.030	-9.41	-0.030	-9.35	-0.030	-9.36
dte ²	1.2E-04	5.09	1.2E-04	5.04	1.2E-04	5.06	1.2E-04	5.07
dsdl								
dsdl ²	-0.015	-5.03	-0.015	-5.08	-0.015	-5.04	-0.016	-5.20
dtl	-0.01	-1.83	-0.011	-1.97	-0.012	-2.04	-0.011	-2.03
dtl ²								
asde	-0.029	-11.13	-0.027	-10.61	-0.028	-10.86	-0.028	-10.99
asde ²								
asdl								
asdl ²								
atl dummy	-0.494	-4.66	-0.501	-4.70	-0.497	-4.68	-0.499	-4.69
TT PT	-0.028	-20.52	-0.030	-21.57	-0.029	-20.73	-0.029	-20.71
cost PT			-0.033	-3.23	-0.058	-4.66	-0.058	-4.65
asde PT	-0.022	-5.93	-0.021	-5.80	-0.021	-5.86	-0.021	-5.73
asdl PT	-0.014	-4.03	-0.014	-3.94	-0.014	-3.98	-0.013	-3.86
Log(ASC)		-15713		-15713		-15713		-15713
LogL		-15170		-15129		-15112		-15110
PseudoRho2		0.035		0.037		0.038		0.038
VoTcar		26.57						
VoTcarcom				21.80		24.46		25.29
VoTcar no c				11.93		5.29		5.36
VoT PT		24.00		54.35		30.58		30.61

Using model RF03 as a base, we estimated various models in order to determine the existence of non-linear sensitivities towards costs. In order to do this, we used an approach in which piece-wise linear segments of cost attributes were defined for which parameters were estimated. We varied both the number of segments and the boundaries of the segments. In this section, we present a selection of the estimation results.

Figure 5.7 shows the cumulative distribution of the charges that were shown to respondents in the stated choice experiment. The height of the charges depends on the trip length reported by respondents. Based on this distribution, the starting segmentation for the piece-wise linear models (NLRF01) was to use six segments, five segments of 1 euro and one segment for charges larger than 5 euro.

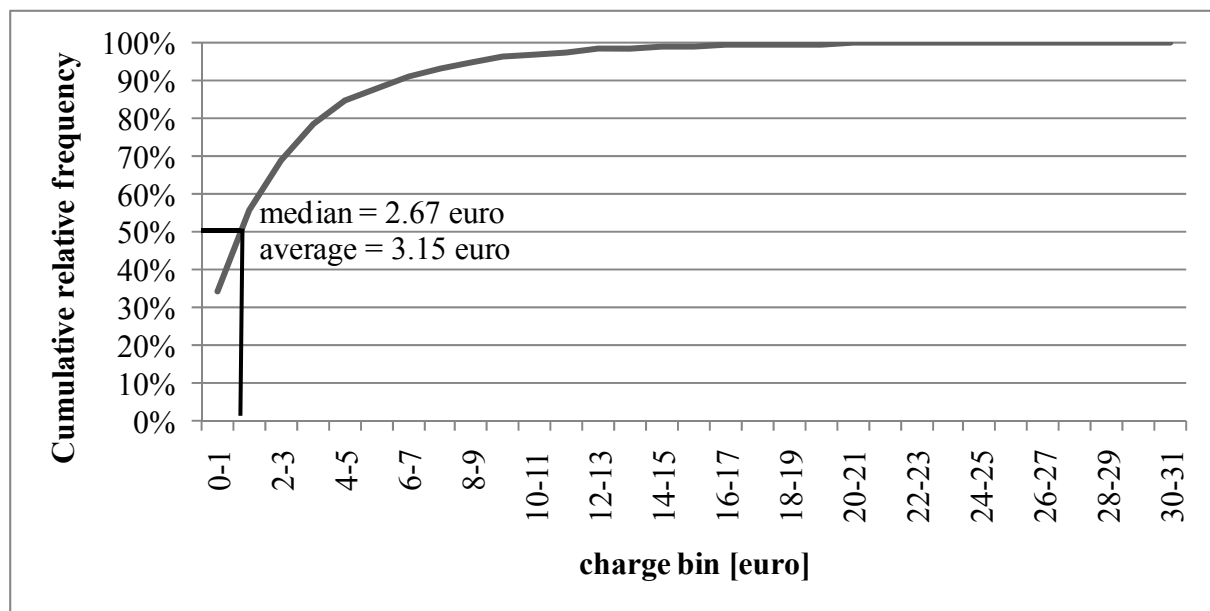


Figure 5.7: Cumulative relative frequency distribution of charges shown to respondents

Based on the analyses of the estimation results of NLRF01 and comparable models, a second model is presented in this section (NLRF02) in which the charges and fuel cost attributes are linear, but an additional charge attribute is included. When charges are higher than 4 euro, this attribute is equal to the amount above 4 euro. The third and last model presented here (NLRF03) uses log transformations for the fuel costs as well as the charge attributes in the car utility function.

Table 5.13: Description of models with non-linear specifications cost attributes

Model name	Base model	Non-linear cost attributes
NLRF01	RF03	6 charge segments (0-1,1-2,2-3,3-4,4-5,>=5)
NLRF02	RF03	Charge >4 attribute
NLRF03	RF03	Log transformations of cost attributes

Table 5.14 shows the estimation results for the three models presented above. For model NLRF01, it appears that, even though the low charge segments are not significant, the sensitivity towards the road pricing charges increases with higher charge levels. Figure 5.8 shows how the utility resulting solely from the charges develops. For each segment, the midpoint is taken, and for the larger than 5 euro charge, a charge of 8 euro. It is again

apparent that the respondents who receive compensation for travel costs have higher utility than those who receive no compensation. Looking at both curves, they seem to have a somewhat similar shape. It could be an S-shape or two linear segments that cross at a charge of about 4 euro. We tested the latter in model NLRF02.

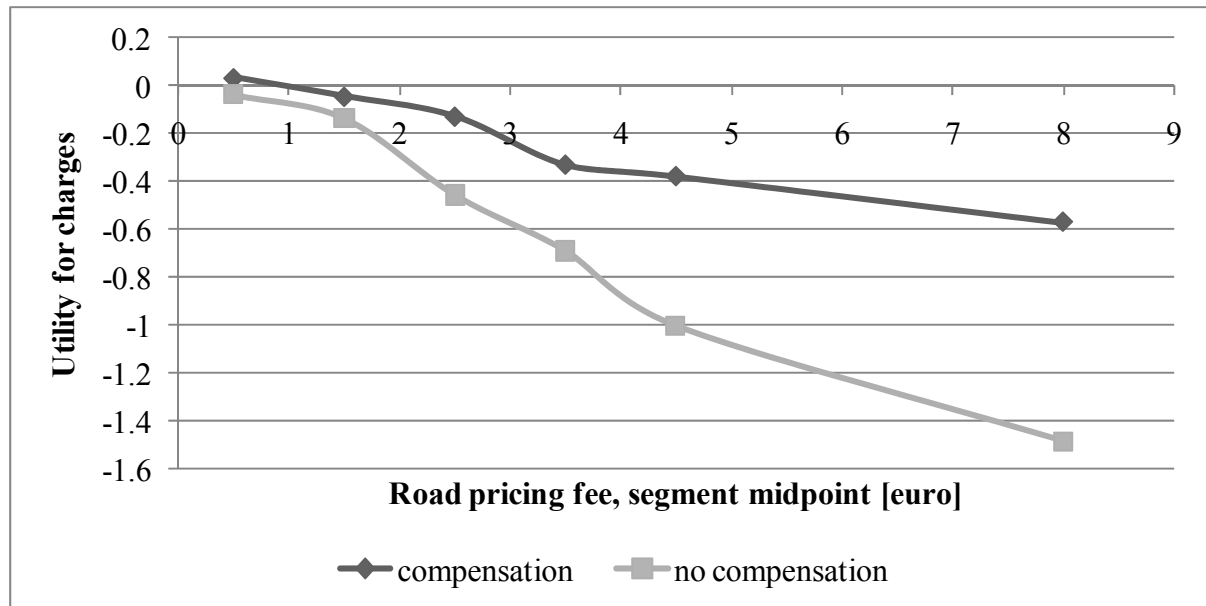


Figure 5.8: Utility of charges in different segments of model NLRF01

Looking at the estimation results of model NLRF02, we see that for charges above 4 euro, the sensitivity of an extra euro charge decreases. This was also apparent in Figure 5.8. In model NLRF02, the charge dummy becomes insignificant, while the differences in ASCs become somewhat lower. The model fit of model NLRF02 seems better than of model NLRF01, with a higher loglikelihood value using fewer parameters. In model NLRF03, we use log transformations of the cost attributes. We see that the sensitivity towards the log of fuel costs is higher than for charges; this is unexpected. Also, some of the scheduling parameters become insignificant. Given these results we prefer model NLRF02 above NLRF03.

Table 5.14: Estimation results for non-linear cost sensitivity models

	Reference		RF03		NLR01		NLR02		NLR03	
	Par	T-value	Par	T-value	Par	T-value	Par	T-value	Par	T-value
ASC_A	0.414	4.13	0.678	5.93	0.718	6.19	0.820	6.95	0.883	7.52
ASC_B	0.548	5.33	0.708	5.85	0.722	5.96	0.740	6.07	0.849	7.02
ASC_C	1.026	10.18	1.171	9.73	1.177	9.69	1.111	9.13	1.154	9.31
Total cost	-0.066	-11.29								
fuelcost			-0.166	-8.62	-0.168	-8.74	-0.166	-8.68		
log(fuelcost)									-0.382	-6.52
charge comp			-0.075	-10.65			-0.167	-9.16		
ch>4 comp.							0.104	5.41		
log(chcomp)									-0.238	-7.95
ch0-1 comp					0.070	0.99				
ch 1-2 comp					-0.029	-0.86				
ch 2-3 comp					-0.051	-2.15				
ch 3-4 comp					-0.094	-4.74				
ch 4-5 comp					-0.084	-4.79				
ch >5 comp					-0.071	-8.60				
charge no c			-0.188	-10.64			-0.297	-8.30		
ch>4 no c							0.135	2.61		
log(ch no c)									-0.301	-6.81
ch 0-1 no c					-0.078	-0.57				
ch 1-2 no c					-0.092	-1.34				
ch 2-3 no c					-0.183	-3.43				
ch 3-4 no c					-0.197	-3.72				
ch 4-5 no c					-0.223	-4.56				
ch >5 no c					-0.185	-9.86				
chdummy			-0.099	-2.22	-0.168	-2.95	-0.018	-0.37	-0.282	-6.10
eTT car	-0.029	-24.77	-0.032	-21.11	-0.032	-20.87	-0.031	-20.32	-0.028	-18.55
dsde			0.008	3.84	0.008	3.55	0.007	3.37	0.006	2.82
dsde ²			-8E-05	-3.25	-7E-05	-2.95	-7E-05	-2.74	-2E-05	-1.02
dte			-0.030	-9.36	-0.030	-9.34	-0.030	-9.39	-0.031	-9.78
dte ²			1E-04	5.07	1E-04	5.05	1E-04	5.09	1E-04	5.54
dsdl ²			-0.016	-5.20	-0.016	-5.33	-0.016	-5.40	-0.016	-5.32
dtl			-0.011	-2.03	-0.012	-2.08	-0.012	-2.09	-0.010	-1.81
asde	-0.028	-14.91	-0.028	-10.99	-0.028	-10.96	-0.029	-11.06	-0.032	-12.77
asdl	-0.014	-3.00								
atl dummy			-0.499	-4.69	-0.504	-4.75	-0.512	-4.82	-0.516	-4.86
TT PT	-0.027	-20.61	-0.029	-20.71	-0.030	-20.74	-0.030	-20.73	-0.026	-19.34
cost PT			-0.058	-4.65	-0.059	-4.72	-0.060	-4.79	-0.026	-2.26
asde PT	-0.02	-5.62	-0.021	-5.73	-0.021	-5.71	-0.021	-5.69	-0.022	-5.93
asdl PT	-0.013	-3.73	-0.013	-3.86	-0.013	-3.84	-0.013	-3.81	-0.014	-3.98
Log(ASC)		-15713		-15713		-15713		-15713		-15713
LogL		-15267		-15110		-15100		-15094		-15165

We would now apply the models from Table 5.14 to the example commuter case. Since we are now looking at cost sensitivities, we repeat the road pricing charges that we apply to this commuter in Figure 5.9. In the example, we further assume that the commuter is not compensated for travel costs by his/her employer and we neglect the effect of fuel costs by assuming they are constant for each departure time. When we consider, however, the impact these charge will have on utility compared to the utilities presented for travel time and rescheduling in Figure 5.6, then these charges hardly matter. We, therefore, multiplied all charges by a factor of 5, which results in charges many respondents were not faced with.

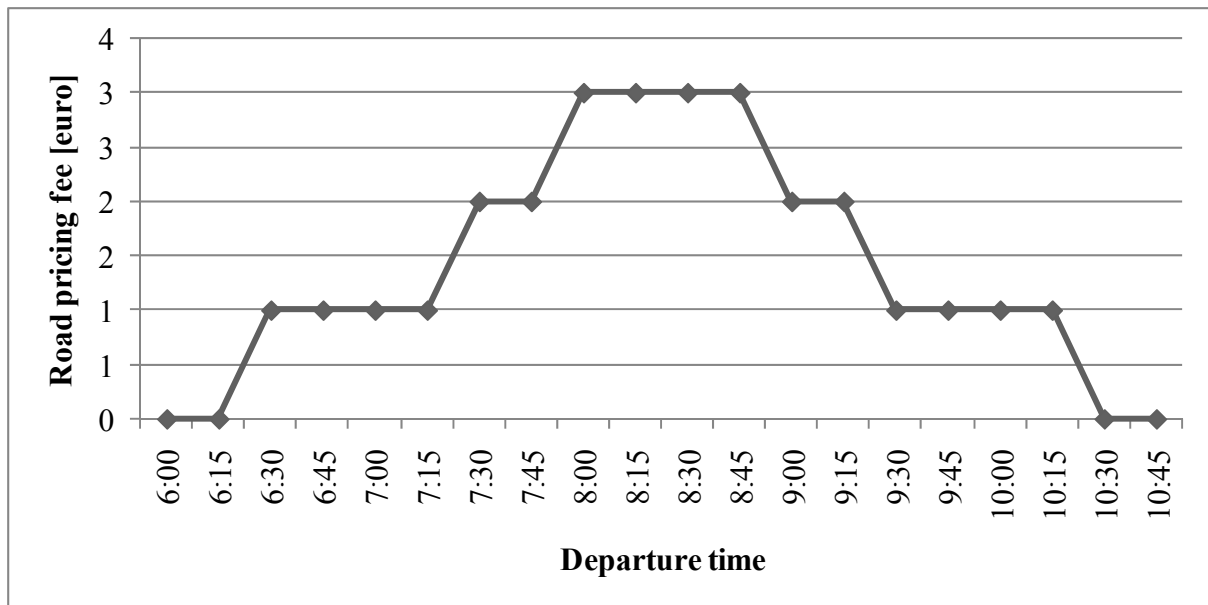


Figure 5.9: Charge levels in example utility calculations

The utility for the different models is presented in Figure 5.10, where we cut off the vertical axis at -24 utility points to make the differences between the models more visible. As a result of the charges, the shape of the utility curves for models NLRFO1 and NLRFO2 are clearly affected, also changing the time period with maximum utility to earlier periods, where the charges are lower but scheduling delays are higher.

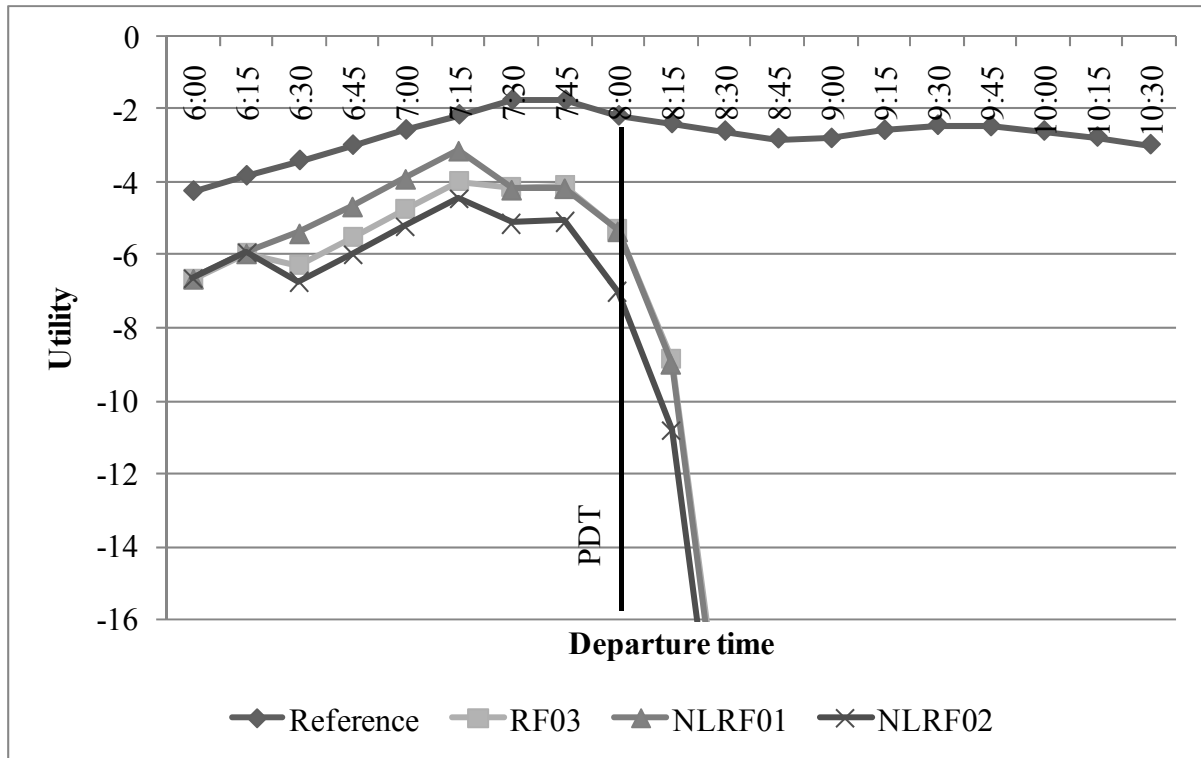


Figure 5.10: Travel utility for example commuter for non-linear cost models

Based on the model results, we conclude that the sensitivity towards different cost components is different and that even a dummy attribute for charges can be significant. This implies that the height of the charge is not the only design dimension which determines the behavioural response. Furthermore, we find non-linear sensitivities toward road pricing charges which also incur more disutility to those who do not receive compensation for home-to-work travel costs from their employer.

5.5 Travel time components

In this section, we will address the remaining attribute in the utility function, namely travel time. We have, up to this point, assumed that all travel time components have the same sensitivity. From the start, we did take into account different sensitivity towards car and public transport, since we know from other studies that this is often the case. So far, however, model results do not consistently show large differences. In this section, we focus on the difference in sensitivity between free-flow travel time and congested travel time. As discussed in Chapter 1, we expect that commuters will have a higher sensitivity towards travel time in congested conditions than towards travel time in non-congested conditions. The next chapter will then focus on the role of travel time unreliability.

As described in Chapter 3, respondents were shown not only the total travel (bandwidth), but this travel time was also split up in a part in free-flow conditions and a part in congested conditions. Besides distinguishing free-flow and congested travel time attributes, we also investigated potential non-linear sensitivities towards these travel time components. We will base the model presented here on the NLRF02 model from the previous section, such that all 3 of the components of utility we specified in Equation (5.4) have been investigated. In the first model (TT01) that is discussed in this section, the car travel time is separated in a free-flow and a congested travel time attribute. In model NLTT01, we use piece-wise linear specifications of both free-flow travel time and congested travel time attributes in order to

assess non-linear sensitivities towards travel time components. In the third and last model (NLTT02), we use log transformations of travel time attributes as an alternative approach for assessing non-linear sensitivities. Table 5.15 presents an overview of the models that are presented here.

Table 5.15: Description of models with varying travel time attributes

Model name	Base model	Non-linear cost attributes
TT01	NLRF02	Separated free-flow and congested travel time attributes
NLTT01	NLRF02	Piece-wise 4 segment free-flow and congested travel time attributes
NLTT02	NLRF02	Log transformations of free-flow and congested travel time attributes

The model estimation results are presented in Table 5.16. The value-of-time estimates that result from these models are presented in Table 5.17, which contains the VoT estimates that can be derived from the models' estimates in Table 5.16. For model NLTT02, which contains log-formulations of travel time components, the partial derivative of the utility function towards time does not result in the parameter value of a travel time attribute. The values-of-time shown here are the mean values found using the travel times used in the stated choice experiment. The resulting values-of-time for all the models are lower than previously found and more in line with values found in the Netherlands by, for example, Hcg (1998).

In model TT01, we see that the respondents indeed have a lower sensitivity towards free-flow than towards congested travel conditions. However, when we try to find non-linear sensitivities towards these travel time attributes, the results are mixed.

In model NLTT01, the free-flow segments that were used in the piece-wise linear approach are all significant and have decreasing values. This implies that with increasing travel times, the disutility of an extra minute of travel time becomes smaller, and this is in line with our expectations. For the congested travel time segments, however, decreasing parameter estimates for longer congested travel times are not as clear. All parameter estimates are again negative and significant, but only the lowest segment of congested travel times between 0-20 minutes appears to have a different parameter value from the other segments. Although the segmentations are different between free-flow and congested travel time, the parameter values seem to indicate that for lower travel times, the sensitivities towards an extra minute of travel time are the same in free-flow and congested conditions. As travel times get longer, however, the sensitivity towards an extra minute of congested conditions becomes larger than an extra minute in free-flow conditions.

When comparing the parameter estimates of model TT01 and NLTT01, we see that the parameter values in TT01 are lower for both free-flow and congested travel time parameters in all segments of the NLTT01 model. This further implies that sensitivity towards an extra minute of travel time is higher for low travel times than for higher travel times. The free-flow travel time and congested travel time log transformations are both significant in model NLTT02. Here, the sensitivity towards the log of free-flow time is larger than for the log of congested time, and we find this counterintuitive.

Table 5.16: Estimation results for alternative travel time attribute models

	NLRF02	TT01		NLTT01		NLTT02		
	Par	T-value	Par	T-value	Par	T-value	Par	T-value
ASC_A	0.820	6.95	0.808	6.86	0.992	7.23	2.617	10.57
ASC_B	0.740	6.07	0.746	6.13	0.860	6.06	2.395	9.65
ASC_C	1.111	9.13	1.124	9.23	1.225	8.71	2.697	11.17
Fuelcost	-0.166	-8.68	-0.165	-8.62	-0.163	-8.46	-0.147	-7.75
charge emp. comp.	-0.167	-9.16	-0.177	-9.32	-0.181	-9.24	-0.168	-9.11
charge>4 emp. comp.	0.104	5.41	0.106	5.51	0.105	5.20	0.129	6.69
charge no comp.	-0.297	-8.30	-0.305	-8.46	-0.309	-8.53	-0.306	-8.57
charge>4 no comp.	0.135	2.61	0.135	2.61	0.131	2.52	0.192	3.79
charge dummy	-0.018	-0.37	-0.014	-0.29	-0.007	-0.15	0.053	1.14
eTT car	-0.031	-20.32						
free-flow TT car			-0.025	-7.92				
fftt 0-15 min					-0.036	-5.52		
fftt 15-30 min					-0.033	-7.51		
fftt 30-45 min					-0.030	-8.04		
fftt >45 min					-0.027	-8.22		
log(fftt)							-0.478	-5.65
eCongTT car			-0.031	-20.31				
ectt 0-20 min					-0.035	-8.89		
ectt 20-40 min					-0.030	-13.13		
ectt 40-60 min					-0.030	-16.03		
ectt >60 min					-0.031	-19.14		
log(ectt)							-0.382	-12.29
dsde	0.007	3.37	0.008	3.46	0.008	3.51	0.008	3.65
dsde ²	-6.6E-05	-2.74	-6.0E-05	-2.48	-6.3E-05	-2.57	-2.1E-04	-8.65
dte	-0.030	-9.39	-0.030	-9.43	-0.030	-9.45	-0.029	-9.12
dte ²	1.2E-04	5.09	1.2E-04	5.13	1.2E-04	5.18	1.2E-04	5.09
dsdl ²	-0.016	-5.40	-0.017	-5.61	-0.017	-5.42	-0.016	-5.17
dtl	-0.012	-2.09	-0.012	-2.05	-0.011	-2.01	-0.011	-1.96
asde	-0.029	-11.06	-0.030	-11.21	-0.030	-11.07	-0.010	-4.24
atl dummy	-0.512	-4.82	-0.509	-4.79	-0.510	-4.80	-0.561	-5.26
TT PT	-0.030	-20.73	-0.028	-17.24	-0.028	-17.26	-0.019	-13.33
cost PT	-0.060	-4.79	-0.059	-4.71	-0.058	-4.67	-0.051	-4.01
asde PT	-0.021	-5.69	-0.021	-5.71	-0.021	-5.68	-0.022	-6.06
asdl PT	-0.013	-3.81	-0.013	-3.82	-0.013	-3.81	-0.015	-4.28
Log(ASC)		-15713		-15713		-15713		-15713
LogL		-15094		-15092		-15086		-15223

Table 5.17 contains the VoT estimates that can be derived from the models' estimates in Table 5.16. For model NLTT02, which contains log-formulations of travel time components, the partial derivative of the utility function towards time does not result in the parameter value of a travel time attribute. The values-of-time shown here are the mean values found using the travel times used in the stated choice experiment. The resulting values-of-time for all the models are lower than previously found and more in line with values found in the Netherlands by, for example, Hcg (1998).

Table 5.17: Car Value-of-Time estimates [euro/h] resulting from models with different travel time specifications

	NLRF02	TT01	NLTT01	NLTT02
VoT car emp. comp	11.04			
VoT car no comp.	3.98			
VoT fft comp		8.57		
VoT ctt comp		10.61		
VoT fft 0-15 min comp			11.84	
VoT fft 15-30 min comp			11.11	
VoT fft 30-45 min comp			9.98	
VoT fft >45 min comp			9.06	
VoT ectt 0-20 min comp			11.55	
VoT ectt 20-40 min comp			9.99	
VoT ectt 40-60 min comp			10.10	
VoT ectt >60 min comp			10.21	
mean VoT fft comp				8.46
mean VoT ctt comp				7.90
fft no comp		3.23		
ctt no comp		3.99		
VoT fft 0-15 min no comp			4.52	
VoT fft 15-30 min no comp			4.25	
VoT fft 30-45 min no comp			3.82	
VoT fft >45 min no comp			3.46	
VoT ectt 0-20 min no comp			4.41	
VoT ectt 20-40 min no comp			3.82	
VoT ectt 40-60 min no comp			3.86	
VoT ectt >60 min no comp			3.90	
mean VoT fft comp				3.13
mean VoT ctt comp				2.92

Parameter estimates from the travel time models are again used to calculate the utilities of different departure times for our example respondent. So far, we have not split up the total travel time into a free-flow and congested part; this is done in Figure 5.11. In Figure 5.12, we then present the resulting utility profiles for different models.

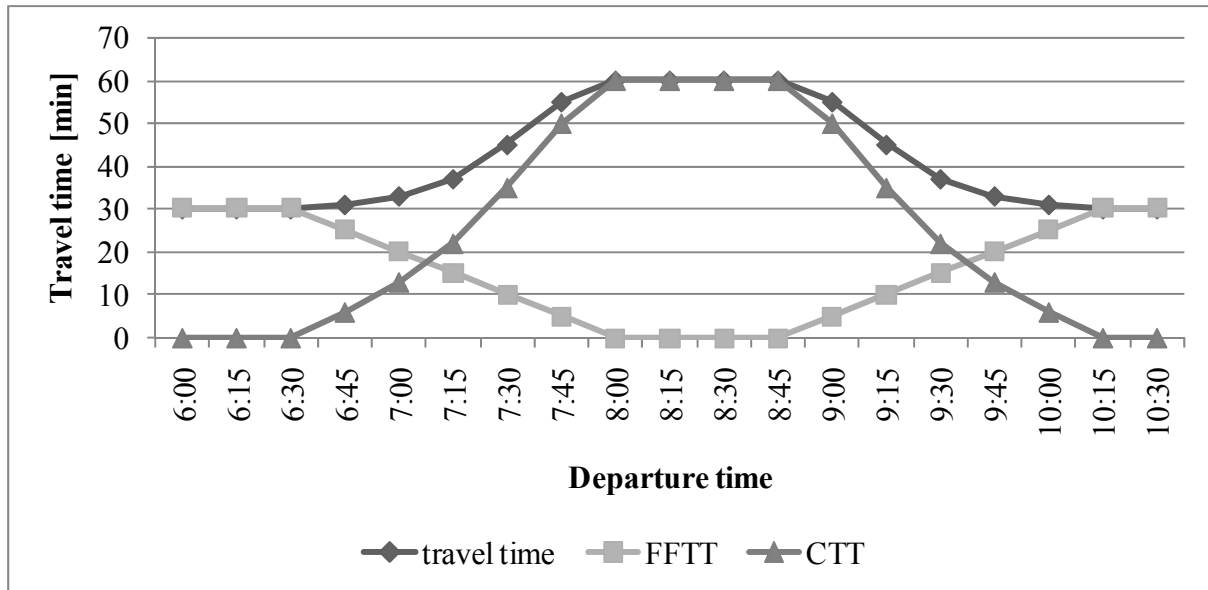


Figure 5.11: Free-flow and congested travel time for example respondent

The sensitivity of free-flow travel time is lower than that of congested travel time, while the generic travel time parameter is about the same as the congested travel time in the model (NLRF02) where the two attributes are not separated. As a result the utility is higher for all departure times in the models where the two travel time attributes are separated. The separation of both attributes will affect the departure time choice of the example commuter, as the time period with highest utility shifts from 7:15 to 7:45 a.m. The differences in utility between time periods 7:15, 7:30, and 7:45 a.m. are, however, smaller than in the model without separation of free-flow and congested travel time.

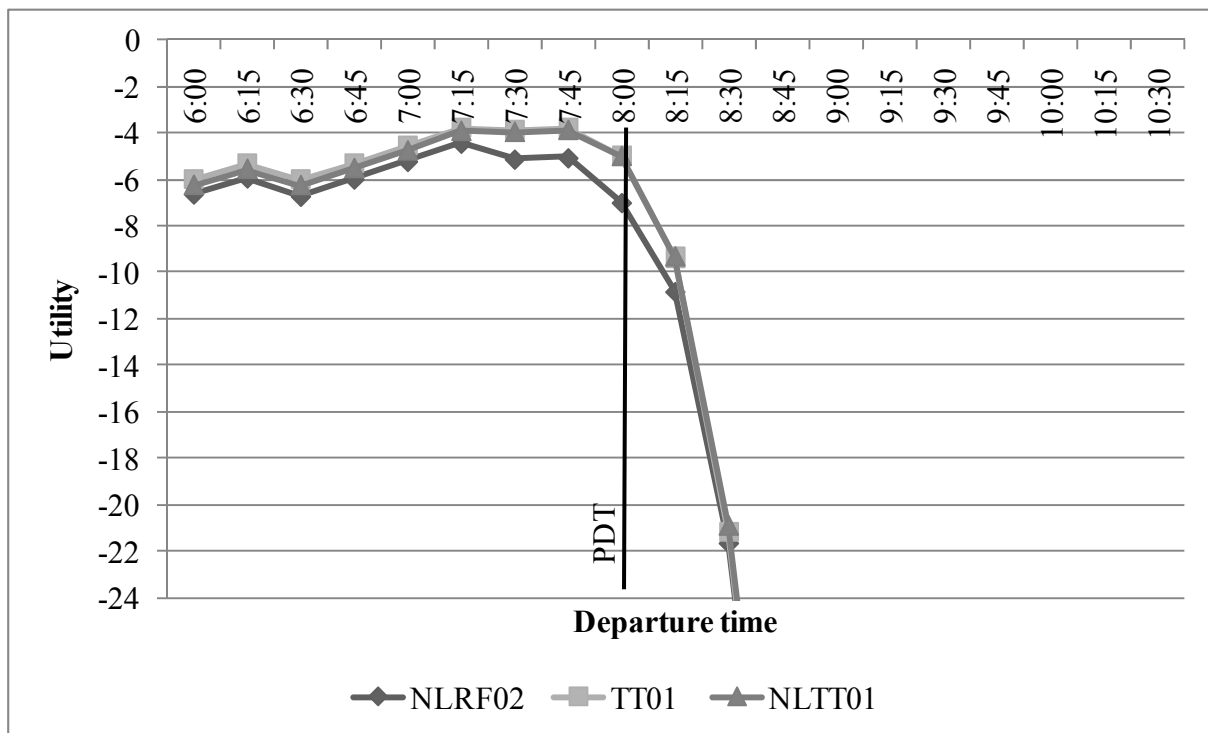


Figure 5.12: Utility for example commuter for models with different travel time attributes

5.6 Conclusions

In this chapter, we have investigated the choice of commuters using the data from the stated choice experiment. Starting from general utility functions for car and public transport, we investigate how sensitive commuters are towards rescheduling, travel costs and travel time. Many models were estimated in this chapter, where the specifications of these three groups of attributes were varied in order to understand the choice behaviour of commuters and to estimate parameter values that we can later use in forecasting the network effects of road pricing measures.

With regard to scheduling components of the general utility function, we found that both departure time rescheduling and arrival time rescheduling are important in departure time choice and that commuters have non-linear sensitivity towards these components. Looking at the utility at different departure times for different models using a constructed example, we see that later departure times incur higher disutility than earlier departure times. This is to be expected for commute trips where most travellers will have to start working at a certain time and other activities are scheduled around working, probably with a lower priority. The distinction between departure and arrival time scheduling delays has previously never been made, but by making this distinction it becomes apparent that the penalties for scheduling early are more dominated by the arrival side of the trip, while for scheduling late, the departure side of trips seems more important. In other words, commuters do not so much mind departing earlier as they do arriving earlier, while at the same time, they are more sensitive to departing late than arriving late.

In our analyses, we found multiple sources of non-linear sensitivities towards rescheduling. First, we found that rescheduling trips outside acceptable departure and arrival time bandwidths incurs additional disutility to respondents. For early rescheduling, we conclude disutility for rescheduling grows more with each extra minute of early departure. Furthermore, when commuters reschedule to times earlier than acceptable to them, this incurs additional disutility. In this case, however, the extra disutility for an extra minute too early departure decreases with every extra minute too early departure. For late rescheduling, we conclude that departing late dominates choice behaviour of commuters, as they are very sensitive to departing late and this sensitivity increases with each extra minute of departing late. We do also find that commuters have a penalty for arriving too late, regardless of the amount of time that they are late.

Scheduling penalties, especially for late scheduling, contribute so much to the total disutility, also when road pricing is included (within margins of reasonable charges), that when road pricing is introduced with the objective to solve traffic problems and with the underlying intended behavioural response of departure time adjustments, the effectiveness of the time-varying road pricing measure must be increased by introducing additional measures that make commuters less sensitive to rescheduling.

Looking at the second group of attributes in the general utility function, we see that commuters have unequal sensitivity towards fuel cost, road pricing charges and public transport cost. They are most sensitive to road pricing and least sensitive to public transport costs. We also find that it is of key importance to take into account whether or not respondents are currently compensated for their commute costs by their employers. Respondents who are compensated are much less sensitive towards the road pricing fee than those who are not compensated. We expect that respondents who are currently receiving

compensation for travel costs may expect to be compensated for road pricing fees as well. In order to increase the effectiveness of the road pricing measure, it will be important to introduce additional policies that reduce the compensation of road pricing fees by employers. We also find that commuters have non-linear sensitivities towards fuel costs and road pricing fees. We find that there is a lower sensitivity for extra charges above a charge of 4 euro. This means that the effectiveness of an extra euro in charges may decrease above a charge of 4 euro. In some of the models, we found a dummy for road pricing fee (=1 if road pricing exists) to be significant, implying that regardless of the road pricing fee, there is extra disutility associated with road pricing as such. This may be explained and influenced by some of the secondary design dimensions of the road pricing measure. Depending on how the road pricing measure is presented or described, commuters may, even if they do not have to pay, associate disutility to an alternative where the measure applies.

The last component of the general utility function we examined was the travel time component. We found that travellers are more sensitive towards congested travel conditions than free-flow travel conditions. This difference in sensitivity increases with higher travel times. With free-flow travel time, more with than congested travel time, the sensitivity of an extra minute of travel time decreases. The sensitivity towards travel time is thus non-linear. This implies that every minute of congested travel time that is saved results in an equal amount of benefit for the traveller, while for free-flow travel time reductions, this is not the case.

6 Travel time unreliability in departure time choice

6.1 Introduction

In the previous chapter, we investigated the influence of scheduling delay, travel cost and travel time attributes on the choice behaviour of commuters. In Chapter 5, however, we used specifications of travel time and scheduling delays neglecting travel time unreliability. As discussed in Chapter 1, travel time unreliability may be an important attribute in the choice behaviour of commuters. It was therefore included in the stated choice experiment we conducted, and, in this chapter, we investigate if and to what extent travel time unreliability may affect the time choice of commuters, in particular in relation to the introduction of road pricing. The behavioural changes as a result of road pricing are likely to cause changes in network performance (flow levels, travel times, etc), thus indirectly influencing travel time unreliability as well. Travel time unreliability expresses the unpredictable variability in day-to-day trip travel times leading to uncertainty for travellers about travel times and arrival times for given departure times. The disutility that commuters experience as a result of travel time unreliability may affect the behavioural changes induced by road pricing, especially related to departure time choice. Furthermore, the behavioural changes due to road pricing are likely to cause changes in network performance, thus indirectly influencing travel time unreliability.

The objective of this chapter is twofold: 1) to determine the appropriate specification of travel time unreliability attributes in utility functions, and 2) to determine the sensitivity of commuters towards travel time unreliability for a morning commute trip. For both objectives, the approach is to estimate choice models with different specifications of travel time, travel time unreliability and scheduling delay. The specification of travel time unreliability in such models and the manner in which it may affect choice behaviour are both, however, still topics of research. There are three major issues involving travel time unreliability: 1) the definition of travel time unreliability and its specification as a disutility component, 2) how sensitive travellers are towards travel time unreliability, and 3) how travel time unreliability can be measured in stated choice experiments in a realistic manner.

Using the data from the stated choice experiment, we estimate choice models with different attribute specifications of travel time, travel time unreliability and scheduling delays. We base the different specifications on a literature review on modelling travel time unreliability. Secondly, based on the most plausible specifications, we derive best estimates of behavioural parameters, among which are values of travel time and travel time unreliability.

We show that besides a scheduling effect, travel time unreliability is a separate source of travel disutility, the level of which depends on the chosen specifications of travel time, travel time unreliability and scheduling delays.

The outline of this chapter is as follows. We start with an introduction into the concept of travel time unreliability and we then present a concise review of modelling approaches concerning alternative concepts of travel time unreliability that try to identify its contribution to departure time choice.

6.2 Travel time unreliability

In transport networks, travel times between origins and destinations vary due to variations in demand and in supply. Weather conditions, accidents, road construction, and congestion levels affect the capacity of the network. At the same time, the travel demand is constantly changing. The resulting variations in travel time may be identified on different levels of aggregations of time, ranging from within day changes in travel times to seasonal and yearly changes in travel times. In general, travel times can be assumed to be stochastic following a certain probability distribution that is known from history (but may change in the future). Depending on the ability to forecast variability in travel times based on experience, information services, etc, the travel times become unreliable. We consider travel time unreliability to be a source of disutility for travellers, caused by the inherent variability of travel time, which leads to uncertainty for travellers in terms of when, where and how to travel. Eliasson (2004) distinguishes three sources of disutility related to the concept of travel time unreliability, namely, travel time variability, unexpected delays and queue driving. The first source, travel time variability, relates to the (predictable) variation in travel time as a result of recurrent levels of congestion within a reasonable period of consideration. The second source, unexpected delays, relates to the inconvenience of on-trip specific incidents that are highly unpredictable and often cause significant delays. The third and last source, queue driving, relates to the inconvenience of not being able to drive at a self-chosen high speed. Noland and Polak (2001) also distinguish different sources of travel time variability, and note that variability is not the same as unreliability, as recurrent congestion may be quite dependable.

The essence of travel time unreliability is that travel time becomes unpredictable for a specific trip as a result of travel time variability. The unreliability of travel times affects the decision-making of travellers, as they will have to take into account a travel time, for different travel alternatives, that they know will not be precisely the travel time they experience when they choose that alternative. When travel times become unreliable, travellers have to take a chance and make decisions that involve risk. In recent years, considerable attention has been given to the influence of travel time unreliability on the choice behaviour of travellers. Noland et al. (1998) describe two sources of inconvenience of travel time unreliability that affect choice behaviour: first, an expected scheduling cost because of not being able to travel at one's preferred timings, on the basis of which travellers value the likelihood of arriving on-time; and, secondly, a planning cost, which represents the inconvenience of the inability to

precisely plan one's activities. With enough experience, a traveller might be able to deduce where the mean or median of the distribution is. This is the travel time a traveller might expect to occur. For trips that require on-time arrival, it is not sufficient for travellers to take this expected travel time into account when choosing a departure time, because in many cases travellers will arrive too late. The traveller, therefore, has to take into account a higher travel time that provides enough confidence in on-time arrival. One of the questions in researching travel unreliability is whether unreliability is an independent component in the valuation of travel time (similar to waiting time, transfer time and in-vehicle time in public transport trips), or whether, instead, the value of travel time unreliability is completely covered by the valuation of the implied schedule delays ('early' and 'late') of trips.

6.3 Modelling travel time unreliability

In modelling the impacts of travel time unreliability on choice behaviour, we need assumptions and hypotheses on how travel time unreliability may affect choice behaviour. When travel time variability increases, the expected travel time also increases. Figure 6.1 shows how travel time variability and unreliability can be included in the decision-making of travellers. On the horizontal axis again is time, where the difference between the preferred departure (PDT) and arrival time (PAT) is again the free-flow travel time. Now that travel times are unreliable, there exists an expected travel time, which is the average expected condition based on the experiences of the traveller. In choosing a departure time, the traveller may, however, need to take into account a longer travel time so that he/she increases the probability of on-time arrival. We call this the anticipated travel time.

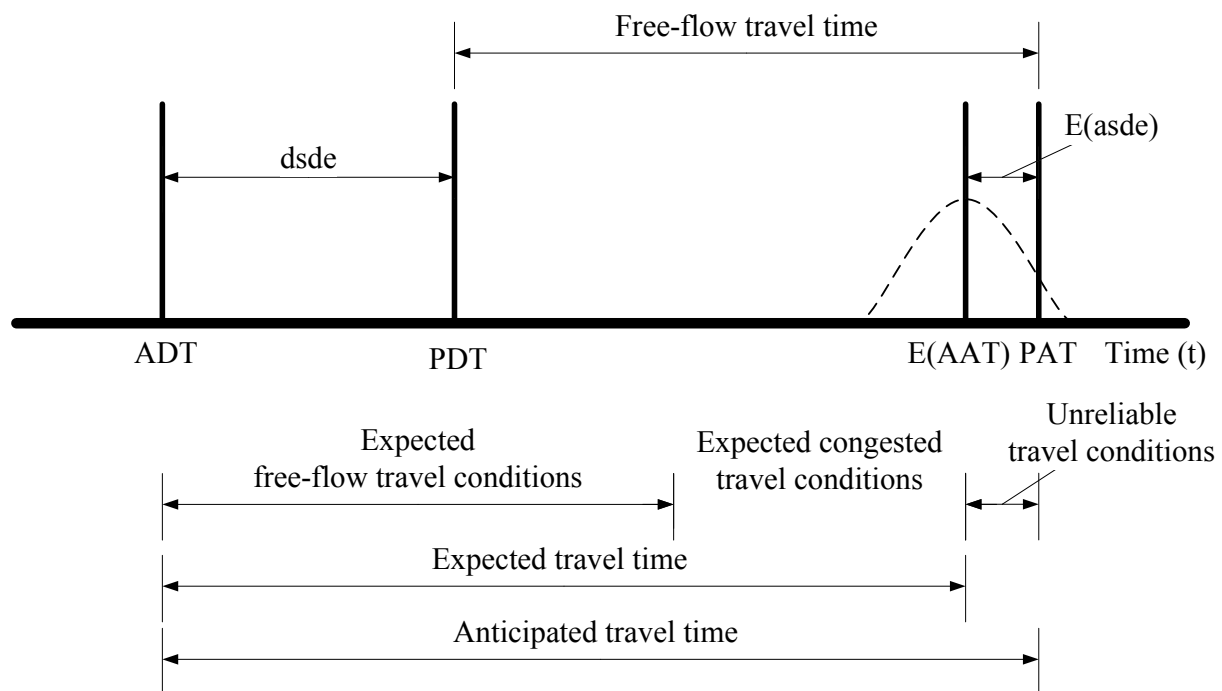


Figure 6.1: Travel time unreliability and rescheduling

This anticipated travel time consist of three parts, namely: a part in free-flow conditions, a part in congested conditions, and a part of unreliable (congested) conditions. In Chapter 5, we found that sensitivity towards free-flow travel time is different than sensitivity towards congested travel time. It is not unlikely that the unreliable congested part of travel time has a different sensitivity as well. However, as the difference between the anticipated travel time and the expected travel time grows, the chances increase of arriving early, thus this unreliable

travel time part can also be interpreted as an expected early arrival rescheduling. In the traditional scheduling approach we also used in Chapter 5, the congested travel time and the rescheduling attributes are both included in the utility function, implying that there is disutility associated with congested travel conditions and rescheduling even though the two attributes describe the same phenomenon of increased travel times. Travel time unreliability impacts the expected travel time, the anticipated travel time and the scheduling delays. Two views on modelling travel time unreliability exist that look at travel time unreliability as either an extra travel time attribute or as a scheduling attribute. These views are: 1) the mean-variance approach, and 2) the scheduling approach. Hollander (2006) and De Jong et al. (2004) provide useful overviews of these different approaches to modelling unreliability. Below we present a short description of both methods.

6.3.1 Direct mean-variance approach

The mean-variance approach addresses the unreliability of travel time as a direct source of inconvenience. This approach hypothesizes that apart from the travel time disutility, its variation at trip level adds a separate disutility to the trip. In the literature, it is referred to as the ‘mean-variance’ approach because, in most examples (Black and Towriss (1993); Jackson and Jucker (1982); Eliasson (2004), Polak (1987), Senna (1994)), the mean travel time and the variance of travel time are both included in the utility function. Since the mean is influenced by extreme values and outliers, some researchers have used the median of travel time and the difference between a percentile (the 90th) and the median (see for example Brownstone and Small (2005), Brownstone et al. (2003), Lam and Small (2001)). The mean travel time is directly influenced by the unreliability of travel time when the travel distribution is, as is typical, not symmetric but skewed to the right. A median-percentile approach avoids this dependence to some extent.

6.3.2 Indirect scheduling approach

In the scheduling approach, the inconvenience of unreliability in travel time reflects the inconvenience of earliness and lateness, as perceived by travellers. So, the travel time uncertainty is transformed into uncertainties in departure time, arrival time, or both. The scheduling approach has been applied by, amongst others, Bates et al. (1995), Gaver Jr. (1968), Knight (1974); Noland et al. (1998), Small et al. (1999). If travel times are highly unreliable, travellers may change their departure time such that the penalties of expected early or late arrival are minimal. The scheduling framework presented by Small (1982) has more or less become the standard approach. The departure time model he proposes includes a travel time attribute, a travel cost attribute, and three trip scheduling attributes. It should be noted that all scheduling components are based on the preferred arrival time of the trips and include a scheduling delay early (0 or # minutes earlier than preferred), a scheduling delay late (0 or # minutes later than preferred), and a lateness dummy (equal to 1 if late arrival).

When travel time unreliability is introduced in this approach, the arrival time of the trip becomes uncertain and an expected arrival time is used in the model. As a result, expected scheduling delays early and late are also used in the model. As we will show later in this chapter, the mean travel time variable and the schedule delay variables may jointly cause the separate unreliability variable to be insignificant in these types of scheduling choice models, resulting in the conclusion (for example, Hollander (2006)) that unreliability is not a separate variable in the choice behaviour of travellers.

Noland et al. (1998), Small et al. (1999) conclude that including a separate variable for unreliability of travel time often turns out to be significant only when scheduling variables are

not present in the utility function. Travellers seem to take unreliability into account entirely through earliness and lateness variables. This finding would advocate for the scheduling approach above the mean-variance approach, although the mean-variance models are more commonly applied. Hollander (2006) supports the scheduling approach for modelling travel time unreliability, stating that the mean-variance approach leads to an underestimation of the value of unreliability. In this chapter, we will test models using both the mean-variance and the scheduling approach with different specifications of travel time and scheduling attributes. The scheduling approach allows for a modelling of travel time unreliability that takes into account both the expected scheduling cost and the planning cost.

6.4 Tests of utility specifications including travel time unreliability

In this section, we cover the first of two objectives of this chapter, namely to determine how travel time reliability can best be incorporated in the choice models as they were estimated in the previous chapter. As discussed in the previous section, we will adopt a scheduling approach in which we will vary both scheduling and travel time attributes to investigate where to include travel time unreliability in the utility function. As a starting point, we again define a reference model, from which we derive alternative specifications of utility functions. We then compare these against each other and against the reference model. Before discussing the reference model, we present some search directions for alternative specifications of utility functions.

Adding travel time unreliability into the scheduling utility function approach raises some questions which find their origin in the fact that travel time unreliability affects both the travel time and arrival time of travellers, while both are already variables in the utility function. These questions can for example be formulated as:

- Is travel time unreliability a separate source of disutility being valued independently from travel time and scheduling delay components, which therefore needs to be included in the utility function?
- Is it sufficient to use expected travel times and expected scheduling delays to take travel time unreliability into account, or can the model be improved by introducing a separate variable for unreliability?
- How does a mean variance model (no scheduling delay components) compare to a scheduling model?

The main issue stemming from these questions is which attributes to include in the utility function in order to incorporate travel time unreliability. There are several possible attributes that relate to travel time unreliability: travel time, travel time bandwidth/variance/unreliability and (arrival time) scheduling delays. Below, we discuss each of these attributes and their relation to travel time unreliability separately.

6.4.1 Travel time variable

It is clear that travel time itself is the source of unreliability. Travellers will associate some disutility to travelling, but different types of travel time may be valued differently. In the previous chapter, we have shown that commuters are more sensitive to congested travel time than free-flow travel time. So is there a case for commuters valuing expected travel time differently than unexpected travel time? And what is expected travel time in that case, does that not already include some of the travel time unreliability? How predictable is travel time unreliability?

These are some questions that may lead to different specifications of travel time in the utility function. The travel time attribute can be defined at any value between the minimum and maximum travel time shown to respondents. Assuming different distributions of travel time, there can be different definitions of mean and median, etc. Figure 6.2 shows some of the possible specifications of travel time in the utility function. The minimum, expected and maximum travel times are shown assuming either a normal or uniform travel time distribution within the given minimum and maximum travel time.

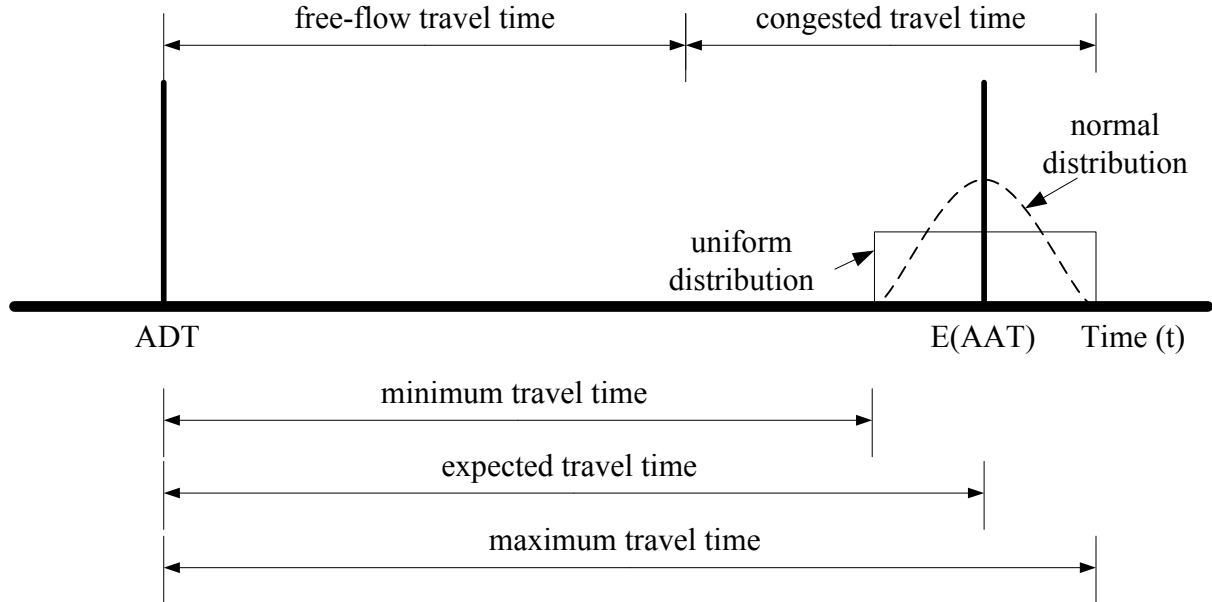


Figure 6.2: Travel time components and potential specifications

In this chapter, we consider only a limited number of travel time specifications. We assume, in most cases, a uniform distribution of travel time, since this is what we have asked our respondents to do. In Appendix B, results are presented for a case where we assume differently shaped triangular distributions of travel time. Assuming a uniform distribution of travel times between the shown minimum travel time τ_{ix}^- and the maximum travel time τ_{ix}^+ , we computed the expected travel time τ_{ix} according to Equation (6.1).

$$\tau_{ix} = \frac{\tau_{ix}^- + \tau_{ix}^+}{2} \quad (6.1)$$

We will use all three specifications of travel time τ_{ix}^- , τ_{ix}^+ and τ_{ix} in the model tests.

6.4.2 Arrival time scheduling delay variables

The scheduling delays are differences between the actual arrival time and the preferred arrival time. Because the actual arrival time is unreliable, the scheduling delays become unreliable. In Chapter 5, we calculated the arrival time scheduling late based on the earliest arrival time and the arrival time scheduling early on the latest arrival time shown to respondents. When taking into account travel time unreliability, the scheduling delays can also be calculated as expected scheduling delays, based on the expected arrival time (Figure 6.3).

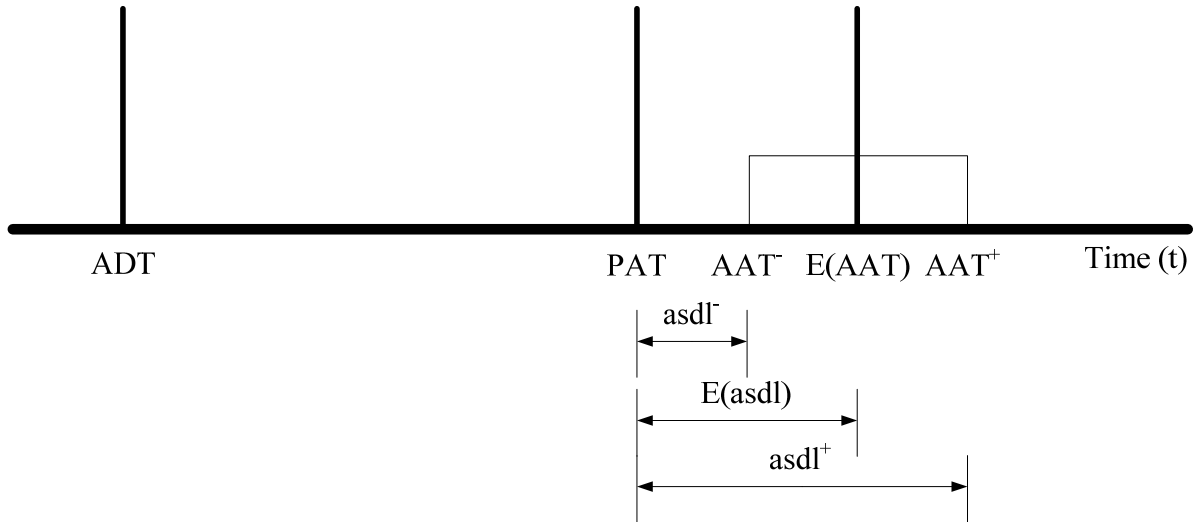


Figure 6.3: Arrival time scheduling delay late

The expected scheduling delays for the car alternatives depend on the expected arrival time (EAT) and the preferred arrival (PAT) reported by respondents. The expected arrival time is, however, also not directly shown to respondents. We then computed the expected arrival time as in Equation (6.2).

$$EAT_{ix} = ADT_{ix} + \tau_{ix} \quad (6.2)$$

We then used the expected arrival time EAT_{ix} to calculate expected arrival time scheduling delays. There are, however, three cases to be considered:

PAT_i is later than the latest arrival time shown AAT_{ix}^+ to respondents. In this case, it is clear that $esdl_{ix} = 0$. The $esde_{ix}$ is calculated according to Equation (5.7) ;

PAT_i is earlier than the earliest arrival time shown AAT_{ix}^- to respondents. In this case, it is clear that $esde_{ix} = 0$. The $esdl_{ix}$ is calculated according to Equation (5.8);

PAT_i is between the earliest arrival time AAT_{ix}^- and latest arrival time AAT_{ix}^+ . In this case, $esdl_{ix}$ and $esde_{ix}$ may both occur with different probabilities. The $esdl_{ix}$ and $esde_{ix}$ are calculated according to Equations (6.5)-(6.7).

Any of the above situations may occur simultaneously within one choice situation.

$$esde_{ix} = PAT_i - EAT_{ix} \quad (6.3)$$

$$esdl_{ix} = EAT_{ix} - PAT_i \quad (6.4)$$

$$esde_{ix} = \frac{PAT_i - AAT_{ix}^-}{2} \cdot (1 - P_l) \quad (6.5)$$

$$esdl_{ix} = \frac{AAT_{ix}^+ - PAT_i}{2} \cdot P_l \quad (6.6)$$

$$P_l = \frac{AAT_{ix}^+ - PAT_i}{AAT_{ix}^+ - AAT_{ix}^-} \quad (6.7)$$

Travel time unreliability

In the stated choice experiment, we show respondents a bandwidth of travel times and associated arrival times. The size of this bandwidth was an attribute in the experimental design of our survey (see Chapter 3) and it is this attribute that we will use as a measure of travel time unreliability. We can either use the bandwidth attribute directly in the utility function (Equation (6.8)) as a measure of travel time reliability or we can calculate a travel time variance by assuming a uniform distribution (Equation(6.9)).

$$v_{ix} = \tau_{ix}^+ - \tau_{ix}^- \quad (6.8)$$

$$Var(\tau_{ix}) = \frac{(\tau_{ix}^+ - \tau_{ix}^-)^2}{12} = \frac{v_{ix}^2}{12} \quad (6.9)$$

We will use both specifications of travel time unreliability in the model tests.

6.4.3 Reference model specification and modelling plan

We have now established alternative specifications of travel time, travel time unreliability and scheduling delay attributes in order to test different model specifications. We use a similar reference model as in Chapter 5, but both departure time and arrival time scheduling delays were already included in this reference model. The estimation results for the reference model are presented in Table 6.1. As we expected from results in the previous chapter, we see that not all the scheduling attributes are significant, but for the purpose of the models in this section, this is not so important.

Table 6.1: Estimation results for reference model

	Reference model	
	Parameter	T-Value
ASC_A	0.419	4.18
ASC_B	0.497	4.77
ASC_C	1.002	9.91
Travel cost [euro]	-0.066	-11.05
Expected travel time [min]	-0.032	-20.17
Departure time scheduling delay early [min]	0.002	1.34
Departure time scheduling delay late [min]	-0.087	-5.84
Arrival scheduling delay early [min]	-0.030	-11.35
Arrival scheduling delay late [min]	0.002	0.28
Travel time public transport [min]	-0.029	-20.72
Scheduling delay early public transport [min]	-0.021	-5.90
Scheduling delay late public transport [min]	-0.014	-3.97
Log(ASC)		-15713
LogL		-15249
Pseudo Rho2		0.029
VoT car		28.67

Given the different specifications of attributes, we then combined these to investigate a wide scope of alternative utility specifications. We estimated models for almost the entire space of possible attribute combinations, but here we present five models. In the first model (R01), we only change the arrival time scheduling attributes to expected arrival time scheduling delays. This model corresponds with the idea that travel time unreliability relates to the scheduling of trips and it is not a separate source of disutility. In the second model (R02), we test this

further by adding a travel time variance attribute to model R01. These first two models represent scheduling approach models, and we test a mean-variance model (R03) in the third model. In models R04 and R05, we then test an approach as shown also in Figure 6.1, where travel time unreliability is an extra travel time attribute, as well as a scheduling attribute. The models described here are summarised below in Table 6.2.

Table 6.2: Modelling plan

Attribute	Specification	Ref	R01	R02	R03	R04	R05
Travel time	Lowest travel time					✓	✓
	Expected travel time	✓	✓	✓	✓		
	Highest travel time						
Travel time unreliability	Travel time bandwidth					✓	✓
	Variance (uniform)			✓	✓		
Scheduling delays	Arrival time scheduling delays	✓					✓
	Expected arrival time scheduling delays		✓	✓		✓	

6.4.4 Estimation results

In this section, we present and discuss the estimation results for the five models specified in the previous section. All the estimation results are presented in Table 6.3. In model R01, we changed the arrival time scheduling delay attributes to expected arrival time scheduling delays. As a result, all the scheduling attributes change somewhat in size as well as in the expected travel time and cost attributes. Perhaps the most noticeable difference is that the *dsde* parameter is now significant and positive. Even though the *E(asde)* parameter is negative and significant, we would not expect travellers to gain utility from departing earlier. In such a case, their preferred departure time might need to be changed. In model R02, the travel time variance attribute is added. This attribute turns out to be significant, but positive. We would expect the travel time variability parameter to be negative. As a result of adding the travel time variance attribute to the utility function, the other scheduling parameters change little. In both model R01 and R02, the loglikelihood values decrease when compared to the reference model, indicating that model fit is deteriorating somewhat.

Table 6.3: Estimation results for unreliability test models

Variable	Reference		R01		R02		R03		R04		R05	
	Par	Tval	Par	Tval	Par	Tval	Par	Tval	Par	Tval	Parr	Tval
ASC_A	0.419	4.18	0.442	4.41	0.446	4.44	0.348	3.48	0.425	4.23	0.415	4.13
ASC_B	0.497	4.77	0.568	5.47	0.573	5.51	0.229	2.28	0.527	5.00	0.485	4.50
ASC_C	1.002	9.91	1.017	10.07	1.028	10.16	0.859	8.56	0.989	9.72	0.996	9.74
Cost	-0.066	-11.05	-0.062	-10.15	-0.063	-10.24	-0.066	-11.38	-0.064	-10.30	-0.067	-11.06
TTmin									-0.034	-17.56	-0.032	-19.18
eTT	-0.032	-20.17	-0.034	-17.43	-0.035	-17.56	-0.030	-22.74				
Dsde	0.002	1.34	0.007	3.12	0.006	2.76			0.006	2.68	0.002	1.37
Dsdl	-0.087	-5.84	-0.081	-5.59	-0.078	-5.43			-0.079	-5.47	-0.087	-5.86
Asde	-0.030	-11.35									-0.030	-11.20
Asdl	0.002	0.28									0.002	0.33
E(asde)			-0.028	-9.79	-0.027	-9.50			-0.027	-9.33		
E(asdl)			-0.001	-0.53	-0.003	-1.18			-0.004	-1.25		
TTband									-0.014	-7.58	-0.015	-10.25
TTvar					0.001	2.09	0.001	2.99				
TT_PT	-0.029	-20.72	-0.029	-20.45	-0.030	-20.45	-0.027	-20.18	-0.030	-20.45	-0.029	-20.51
Asde_PT	-0.021	-5.90	-0.021	-5.78	-0.021	-5.77	-0.019	-5.39	-0.021	-5.78	-0.021	-5.91
Asdl_PT	-0.014	-3.97	-0.014	-3.90	-0.014	-3.90	-0.013	-3.69	-0.014	-3.91	-0.014	-3.98
Log(ASC)		-15713		-15713		-15713		-15713		-15713		-15713
Log L		-15249		-15263		-15261		-15384		-15261		-15249
PseudoR2		0.029		0.029		0.029		0.021		0.029		0.030
VoT car		28.67		32.73		31.06		27.19		32.57		28.85
VoR car						-0.39		-0.54		12.80		13.82

In model R03, we test a mean-variance model approach and all the scheduling attributes have been removed from the utility function. Again, the travel time variance parameter is significant and positive. Besides this behaviourally undesirable result, the model fit also deteriorates substantially. We abandon the mean-variance approach here as we find better behaviourally understandable models using a mean-variance. In model R04, the expected travel time attribute is replaced by the minimum travel time (which includes congestion) shown to respondents, and the travel time bandwidth attribute was added as a measure of travel time unreliability. Expected arrival time scheduling attributes were used. The estimation results show parameter estimates for scheduling and travel time attributes similar to those in the previous models. The bandwidth parameter is, however, significant and negative. The sensitivity towards the travel time bandwidth is about a third of the sensitivity towards travel time. Still, the loglikelihood value of model R04 shows some deterioration in model fit. In model R05, the expected arrival time scheduling delay attributes are replaced by the arrival time scheduling attributes from the reference, compared to model R04, and we then find similar results as in model R04. The dsde parameter becomes insignificant again, which is behaviourally desirable since the parameter value is positive, and model R05 does not show the deterioration in model fit.

When looking at all the models in Table 6.3, only the reference model and model R05 have expected signs and parameter values for all the significant attributes in the model. In all other models, at least one significant attribute has a positive parameter value. Based on these results, we conclude that using our data and approach for measuring choice behaviour in uncertain conditions in the stated choice experiment, the travel time unreliability can best be included in a scheduling approach using just the expected travel time or using a separate bandwidth parameter and a minimum travel time attribute. The expected arrival time scheduling attributes and variance attributes lead to less appropriate and worse fitting models.

6.5 Behavioural consequences and valuation of travel time unreliability

In the previous section, we investigated alternative specifications for including travel time unreliability in the utility function, alternatively as a part of travel time, of scheduling delays, or as a separate component, and we found that specifying unreliability as a separate component provides good results and gives us the ability to determine sensitivities towards travel time unreliability separately. The latter is the subject in this section.

In this section, we present the estimation results of five different models which vary only in how the travel time unreliability is included in the utility function. Based on the findings in the previous section, we use a scheduling approach together with a minimum travel time attribute, and a travel time bandwidth specification as a measure of travel time unreliability. The models presented in this section were estimated at a different moment than the models presented in Chapter 5, which results in somewhat different specifications of scheduling, cost and travel time attributes in the utility functions.

In the first model (U01), we start with a similar specification of travel time and travel time unreliability as in model (R05) in the previous section. Model U01 and all subsequent models also include different cost and scheduling attributes, some of which are specified as quadratic or log-transformations as well. In model U02, we add a quadratic term for travel time bandwidth, while in model U03, we only use this quadratic term. In model U04, a log-transformation of the travel time bandwidth parameter is tested. In the last model (U05), the three travel time parts are separated in the utility function, as this model has a free-flow, minimum congested travel time and travel time bandwidth attribute. The estimation results of all these models are presented in Table 6.4.

Table 6.4: Estimation results for models including travel time unreliability

Variable	U01		U02		U03		U04		U05	
	Par	Tvalue	Par	Tvalue	Par	Tvalue	Par	Tvalue	Par	Tvalue
ASC_A	1.275	9.20	1.287	9.22	1.176	8.52	2.775	12.56	1.259	9.03
ASC_B	1.236	8.59	1.258	8.53	1.002	7.13	2.760	11.18	1.228	8.53
ASC_C	1.557	11.04	1.578	10.95	1.362	9.79	3.116	12.94	1.555	11.04
TTmin	-0.032	-19.48	-0.032	-19.46	-0.031	-18.72	-0.032	-19.30		
FFTT									-0.030	-9.11
CTTmin									-0.033	-19.31
TTband	-0.016	-10.39	-0.017	-5.98					-0.016	-10.39
(TTband) ²			2.2E-5	0.70	-1.4E-4	-8.27				
Log(TTbnd)							-0.270	-9.13		
Fuelcost	0.022	0.75	0.022	0.76	0.019	0.66	0.025	0.85	0.020	0.67
Charge	-0.067	-8.16	-0.066	-8.12	-0.067	-8.23	-0.062	-7.64	-0.071	-7.63
Ln(Fuelcost)	-0.168	-7.42	-0.168	-7.43	-0.165	-7.31	-0.169	-7.48	-0.165	-7.23
Ln(charge)	-0.137	-3.98	-0.138	-4.00	-0.139	-4.05	-0.146	-4.25	-0.137	-3.96
Ch_dummy	0.459	3.13	0.460	3.13	0.481	3.28	0.496	3.38	0.458	3.12
dsde	0.008	3.46	0.008	3.48	0.007	3.03	0.007	3.05	0.008	3.50
dsde ²	-6.6E-5	-2.72	-6.5E-5	-2.72	-7.1E-5	-2.94	-7.1E-5	-2.97	-6.3E-5	-2.59
dte	-0.031	-9.70	-0.031	-9.69	-0.031	-9.72	-0.031	-9.62	-0.031	-9.71
dte ²	1.3E-4	5.64	1.3E-4	5.64	1.3E-4	5.69	1.3E-4	5.66	1.3E-4	5.66
dtl	-0.010	-1.83	-0.010	-1.81	-0.011	-1.91	-0.009	-1.55	-0.010	-1.80
dsdl	-0.081	-5.55	-0.080	-5.53	-0.083	-5.69	-0.074	-5.06	-0.082	-5.62
asde	-0.029	-11.18	-0.030	-11.19	-0.025	-9.99	-0.026	-10.16	-0.030	-11.12
Log(ATL)	-0.207	-4.38	-0.208	-4.39	-0.215	-4.51	-0.207	-4.37	-0.207	-4.37
PT_cost	-0.050	-4.06	-0.050	-4.05	-0.050	-4.06	-0.049	-4.00	-0.049	-4.00
PT_TT	-0.028	-19.40	-0.028	-19.34	-0.028	-19.06	-0.027	-16.68	-0.027	-16.68
asde PT	-0.021	-5.66	-0.021	-5.66	-0.021	-5.66	-0.021	-5.67	-0.021	-5.67
asdl PT	-0.013	-3.81	-0.013	-3.81	-0.014	-3.96	-0.014	-3.88	-0.013	-3.82
Log(ASC)		-15713		-15713		-15713		-15713		-15713
Log L		-15105		-15104		-15122		-15118		-15104
PseudoRho2		0.039		0.039		0.038		0.038		0.039
meanVoT		29.00		29.23		27.33		30.99		
meanVoFFT										25.31
meanVoCtt										27.67
mean VoR		14.01		14.81		5.37		0.39		13.26

Looking at the estimation results for the different models, we focus primarily on the parameter estimates of the changing attributes. The other parameter values, which are more or less constant between the different models, are of too little interest here to discuss in detail. In

model U01, the travel time and travel time bandwidth parameters are both negative and significant, as we expect from results from the previous section. The sensitivity towards travel time bandwidth (TTband) is about half the sensitivity towards minimum travel time (TTmin). When the quadratic term is added in model U02, this parameter is not significant. The quadratic travel time bandwidth attribute is, however, significant in model U03, where the linear attribute TTband has been removed. The loglikelihood value of this model does, however, indicate that linear specification in model U01 performs better. The log-transformed bandwidth attribute in model U04 is also significant and negative. The mean VoR that results from this model is, however, rather low. Also, the loglikelihood value deteriorates when compared to the model with a linear specification of the travel time bandwidth attribute. From the model results of models U01 through U04, we conclude that there is little to no evidence for non-linear sensitivity towards the travel time bandwidth parameter. This is somewhat surprising, as we did find such non-linear sensitivities to other travel time attributes in Chapter 5. In model U05, three of the travel time parts are included. As expected, the sensitivity towards congested travel time is the largest, followed by the free-flow travel time and then the travel time unreliability.

In all the models presented in this section and the previous section, where we were able to find sensible estimates for a travel time unreliability parameter, we find that it is about half the size of the sensitivity towards travel time. In Table 6.5, we show some of the values of travel time unreliability found in other studies, either values in euro/h or multiplication factors compared to the value of time. We find a value of about 14 euro/h and a factor of about 0.5. We see that the values in other studies are not conclusive. When looking at the different multiplication factors, especially, values are found between zero and one as well as a factor above one. The factor of 0.5 that we find here is on the low side, but it is not impossible, and given the values-of-time found at the end of Chapter 5, the expectation is that multiplication factors between 0.5 and 1.0 will be found using different model specifications on our data. The value of 14 euro/h is more difficult to compare with other studies, as they are more time and context dependent. The values we find are plausible compared to values found elsewhere.

Table 6.5: Reported values of travel time unreliability for car trips

Study	Value of travel time unreliability	Method
Brownstone and Small (2005)	11-14 €/h (male) 28-30 €/h (female)	RP data using percentile and median approach
Lam and Small (2001)	4.65 – 12.29 €/h (male)* 6.03 – 27.58 €/h (female)*	RP data using percentile and median approach *February 2007 exchange rate \$ to €
Senna (1994)	2.50 times VoT	SP data mean-variance approach
Noland et al. (1998)	1.27 times VoT	SP data mean-variance approach
Black and Towriss (1993)	0.55 times VoT	SP data mean-variance approach
Transport Research Centre, Ministry of Transport Public Works and Water management, The Netherlands, 2005a	0.80 times VoT	Expert meetings
Eliasson (2004)	Travel time variability Morning: 3.86 €/h* Afternoon: 1.64 €/h* Value of unexpected delays Morning: 42.15 €/h* Afternoon: 26.70 €/h*	SP data mean-variance approach *February 2007 exchange rate Kr to €

6.6 Conclusions

In this chapter, we investigated alternative specifications of utility functions for including travel time unreliability. We compared a mean-variance with a scheduling approach. For the scheduling approach, we included and combined travel time unreliability in an expected travel time, in expected arrival time scheduling delays and as a separate attribute. Based on the estimation results, we conclude that it is possible to either include travel time unreliability in an expected travel time attribute or as a separate attribute. These findings both support and contradict results found by others. It supports the finding that a scheduling approach is to be preferred over a mean-variance approach, but contradicts the finding that travel time unreliability can be included completely by taking it into account by the scheduling delays. The latter may be caused by many different factors, among which the manner in which travel time unreliability was included in the experiment and the use of departure time scheduling delays may be the most important.

We also investigated the sensitivity of commuters towards travel time unreliability. We found that non-linear terms of unreliability did not improve the models and that the value-of-travel time unreliability is about half that of travel time. We compared our resulting values-of-travel time unreliability to values found in literature, but found that the differences between reported values are large. The values we find are plausible. Further research will still be needed on how the measure sensitivities to unreliability in the stated choice environment, and also on the estimation of sensitivities towards travel time unreliability itself.

The results in this chapter show that travel time unreliability is an important attribute of a travel option and, as such, influencing the travel time unreliability will influence choice behaviour. As a result of road pricing, the demand for travel will decrease and, as a result, traffic conditions will change as well. These changes in traffic conditions, however, may result in higher as well as lower travel time unreliability. When some congestion relief occurs in fully blocked corridors, the travel time predictability may decrease, leading to higher levels of travel time unreliability. In general, we expect that the lower travel times will also lead to a lower level of travel time unreliability.

With this chapter, the research into behavioural responses towards road pricing ends. In the next part of this thesis, Part C, we will use the behavioural models that were estimated in this part to assess the network effects of time-varying road pricing measures. To this end, a modelling framework will be developed and implemented. Unfortunately, the travel time unreliability will not be an explicit part of the research in Part C, as we will not be able yet to quantitatively define the effect of changing traffic conditions on travel time unreliability between different routes, departure times or even modes.

PART C: Modelling network effects of road pricing

This part covers the design, tests and application of the pricing impact model. An analytical dynamic multi-user equilibrium model is used together with departure time choice models and an elastic demand module. The key contributions of this Part are:

- Development of a practical applicable modelling framework that is capable of assessing the network effects of time-varying road pricing measures. The modelling framework explicitly models the departure time and route choice of each user class and determines the changing levels of demand by using an elastic demand model. The interactions between choice behaviour are modelled using feed-back loops in an iterative procedure that result in stable equilibrium conditions.
- Application of the modelling framework to assess the potential network effects of a reward scheme where commuters receive monetary incentives if they do not travel during peak hours. Such a reward scheme, called “Spitsmijden” was tested on a small sample of commuters travelling between the cities of Zoetermeer and The Hague in the Netherlands.

7 Modelling network effects of road pricing

7.1 Introduction

In this chapter, we develop the modelling framework that is capable of assessing the network effects of time-varying road pricing measures. The purpose of this chapter is to identify the key components of the framework necessary to model the desired road pricing measures. The purpose is further to create working models for each component of the framework.

An important issue in identifying the components of the modelling framework is to determine the behavioural responses towards time-varying road pricing measures which are necessary to take into account in the modelling framework. The stimulus-response framework in Chapter 2 provides this insight. For each of the behavioural responses used in the modelling framework, the issues are then to determine what type of choice model to use, and with what attributes and parameter settings.

In this chapter, we find that in order to model time-varying road pricing measures correctly, it is of great importance to correctly model the space-time distribution of traffic in detail, to produce correct estimates of travel times, changes in travel times and behavioural responses as a consequence. The resulting framework, therefore, uses an analytical multi-user dynamic traffic assignment model together with departure time choice and elastic demand. This equilibrium framework recognises the importance of travel times in decision-making, and it does so for different types of users. There are only very few applications of modelling frameworks based on dynamic traffic assignment models with departure time choice and elastic demand. The construction of such a framework is the main contribution of this chapter.

7.1.1 Streams of modelling approaches for road pricing

In modelling the effects of road pricing measures, there are, broadly seen, three streams of models. First, there is a stream of simplistic traffic models which represent, for example, a single bottleneck rather than a complete network. This type of model is often used for economic assessments of road pricing and for determining optimal road pricing measures given different objectives. The complexity of optimisation issues in this research stream requires the traffic model to be fast, often with additional requirements such analytical unique

equilibrium solutions. Yang and Huang (2005) and Button and Verhoef (1998) provide good overviews and examples of this stream of research.

The second stream does take into account complete transportation networks and focuses on complex model structures to correctly determine the demand effects of road pricing and to simplify the route choice and travel time calculations by using static equilibrium assignments. Examples of these approaches can be found in Kim and Hwang (2005), Rich and Nielsen (2007), Eliasson and Mattsson (2001), and Rijkswaterstaat Adviesdienst Verkeer En Vervoer (2005).

The third stream uses dynamic traffic assignment models to determine, in detail, the route choice of travellers at different departure times. The traffic is simulated through the network, where the location and speed of either individual vehicles (microscopic models) or flows (macroscopic models) are updated, for example, every second. The travel times resulting from these models are more accurate, and they depend on the departure time of a trip. Due to the complexity and long run times of dynamic models, the demand is often taken as constant and exogenously determined. Microscopic models, in particular, are very difficult to calibrate and validate, and often require an undesirable number of repetitions with draws from distributions of behavioural parameters, such as speed choice or gap acceptance. De Palma et al. (2005), May and Milne (2000) are examples of research that have used dynamic models for assessing network effects of road pricing.

With time-varying road pricing measures, which are of specific interest in this research, travellers are more likely to adjusting their behaviour based on trade-offs between the travel conditions and costs. The time-varying road pricing costs and time-varying travel conditions together require a model framework that is capable of accurately modelling the flow of traffic and travel conditions.

In this research, the second and third stream are better connected. A dynamic traffic assignment model is used for detailed modelling of travel times and route choice for reasons mentioned above. To this DTA model, we added a departure time choice model and a trip making decision model, the latter in the form of an elastic demand approach. This way both behavioural responses and network conditions are modelled in such detail that the effects of time-varying road pricing measures can be assessed. The DTA model used in this research is an analytical macroscopic multi user class equilibrium model, which is explained in more detail later in this chapter.

In the remainder of this chapter, the different components of the modelling framework are presented in more detail, starting at the heart of the framework, namely the dynamic traffic assignment (DTA) model. The departure time choice and elastic demand modules are built around this DTA model. Both the departure time choice and elastic demand module are discussed in detail in succeeding sections. The framework that results contains two iterative processes which should both reach an equilibrium state. The iterative framework and associated equilibrium issues are then discussed in the final section of this chapter.

The setup of this chapter is as follows. First, the overall setup of the modelling framework is determined in section 7.2. The different model framework components are then discussed in the succeeding sections of the chapter.

7.2 Requirements of the modelling framework

The purpose of developing a modelling framework is to assess the long-term traffic network effects of time-varying, user-class differentiated road pricing measures. In this section, we will discuss the requirements of the modelling framework and determine the components that should be included in the framework. The requirements of the modelling framework are determined by the road pricing measure and its level of differentiation on the one hand and by the expected behavioural responses towards the road pricing measure and changing travel conditions on the other hand.

7.2.1 Requirements from road pricing measures

The design of different road pricing measures place different requirements on the modelling framework. The road pricing measures we are mainly interested in within this research are time-varying and user-class differentiated road pricing measures.

With time-varying road pricing measures, the charge levels change over time. The change over time can have many different levels, ranging from changing the charge levels each year to each second. With time-varying road pricing measure, we mean, in this case, that the price levels change during the day, even within a peak, according to posted charge schedules. The price level thus does not depend on the actual conditions on the road.

The within day level of time differentiation in charge levels will give travellers an incentive to change their departure time towards cheaper time periods. If and how much travellers will actually change their departure time will, among many other factors, depend on the expected travel times of perceived alternative departure time periods. This level of time differentiation therefore places two requirements on the modelling framework: 1) the modelling framework needs to be able to handle time-varying road pricing measures (requirement 1) and 2) the travel times for different departure periods need to be calculated accurately (requirement 2). Note that even with fixed charge levels during the day, people may change departure times as a result of changes in traffic conditions. The necessity of taking into account departure time choice is therefore not limited to a case with within day time-varying road pricing measures.

Another aspect of the road pricing measure is the user-class differentiation. This means that for different groups of travellers, different charge levels may be applied. Different charge levels lead to different behavioural responses. This places two requirements on the modelling framework: 1) charge levels need to be distinguished per user-class, e.g. the user-class concept must be supported by the modelling framework (requirement 3) and 2) each user-class needs its own choice model and parameter settings for each choice process in the modelling framework (requirement 4).

7.2.2 Expected behavioural responses

In this section, the modelling requirements are determined using the stimulus-response framework from Chapter 2 (see Figure 7.1). These frameworks describe the interactions between road pricing measures, individual behavioural responses and system changes. The modelling framework constitutes a mathematical and computerized formulation of these conceptual frameworks, as much and as realistically as possible.

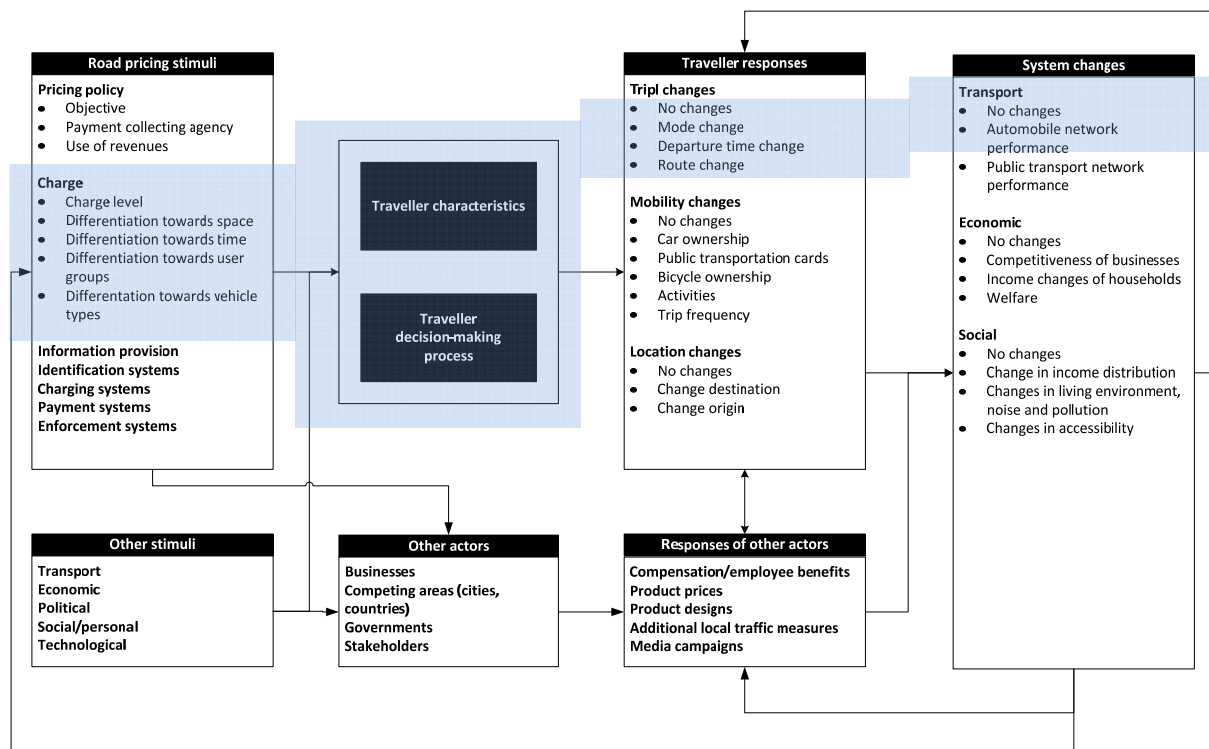


Figure 7.1: Stimulus-response framework

In Chapter 2 of Part A, a stimulus-response framework (see Figure 7.1) was presented. In this framework, road pricing stimuli invoke behavioural responses from travellers which change the performance of the (transportation) system. This, in return, causes behavioural responses. In the long-run, this process is assumed to lead to a new stable equilibrium situation. Reaching stable equilibrium conditions is, therefore, also a requirement of the modelling framework (requirement 5). The modelling framework is required to take into account: 1) changes in car demand levels (requirement 6), 2) changes in temporal distributions of demand (requirement 7) and 3) changes in spatial distribution of demand (requirement 8).

The behavioural responses of travellers may result in different system changes. The stimulus-response framework distinguishes social, economic and transport system changes. The modelling framework focuses only on the transport system changes, although model results may be used as input for other models and analyses. More specifically, the focus is on the changes in performance of the car network. The modelling is thus required to model the changes in car traffic network performance as a result of behavioural changes towards road pricing measures (requirement 9).

7.3 The modelling framework

In the previous section, the requirements of the modelling framework were determined based on the design of the road pricing measures and the expected behavioural responses. The purpose of this section is to develop a modelling framework that meets all the requirements. Given the requirements, many possible model frameworks may still exist, and in this situation, criteria such as computation time, data availability, etc are taken into consideration. Since all of the requirements have to be met, the order in which they are taken into account is unimportant.

Requirement	Description
1	time-varying road pricing measures
2	accurate time-varying travel times
3	User-class charge levels
4	User-class specific choice model
5	Equilibrium
6	Forecast changes in demand
7	Changes in temporal distribution
8	Changes in spatial distribution
9	Car traffic system performance

In order to meet requirements 1, 2, 7 and 9, given within peak changes in charge levels, the model frameworks need to consider time explicitly. This can only be done in an appropriate manner by using a dynamic traffic assignment model.

In a dynamic traffic assignment model, the traffic (flows, packets, or individual vehicles) is assigned to a specific route at a specific departure time and is ‘followed’ in time through the network. At each instant, the amount of traffic on each link is known. As a consequence, the network characteristics can be time dependent, thus allowing for time-varying road pricing measures (requirement 1).

The key objective of DTA models is to accurately model the flow of traffic, and consequently the travel times, in the network. Without accurate travel times, the route choice process is disturbed (requirement 2). Since the traffic demand in a DTA model is put on the network at different departure times, the effects of changes in the temporal distribution of car demand as a result of road pricing can be modelled (requirement 7). In order to model the changes in the temporal distributions, it is necessary to model the departure time choice of travellers. Ideally, the modelling framework would consider the departure time choice and route choice simultaneously in the DTA model, since it is considered jointly by travellers.

Concerning requirement 3 and 4, there are several considerations. Besides user-class specific road user charges and choice models, which can mostly be handled by available DTA models, there is user-class specific driving behaviour and infrastructure availability. For example, trucks drive at different speeds than cars and may use truck lanes. This latter form of user-class specific behaviour is not captured by most dynamic traffic assignment models, especially not in an equilibrium context.

That leaves requirement 6, which requires the modelling framework to take into account changes in demand. Given that the demand changes are the result of many different choice processes, as shown in Figure 7.1, this would mean that the modelling framework needs to include a variety of choice models and interactions in order to model all these changes. When combined with requirement 9, however, this can be simplified. Since we are only interested in the performance of the car network as a result of road pricing, we only need to know how much the demand between each origin and destination changes without knowing why. In order to take into account the changes in demand, we can therefore adopt an elastic demand framework in which the cost changes relative to the reference case without road pricing caused changes in car demand.

To summarize, the modelling framework is constructed using a dynamic traffic assignment model, which is capable of calculating multi-user class route choice equilibriums including

time-varying road pricing measures. This is combined with user-class specific departure time choice models and elastic demand. The modelling framework, furthermore, consists of iterative procedures to reach equilibrium conditions on route, departure time, and elastic demand levels. In the succeeding sections, we present each of the three components in more detail, starting with the DTA model, then the departure time choice model and ending with the elastic demand model. Before we do so, however, we first discuss the overview of the modelling framework, which is presented in Figure 7.2.

As mentioned, the modelling framework contains an iterative procedure. In fact, two feed-back mechanisms are included. In the first feed-back loop, the route flows ($f_p^u(k)$) for each user group u and departure period k are updated given new traffic conditions. This inner loop results in a route choice equilibrium of the current user class u dynamic demand $D_{rs}^{iu}(k)$ in outer loop iteration i between origin r and destination s . The outputs of the traffic simulation are equilibrium travel times ($\tau_p^{iu}(k)$), charge costs ($\theta_p^{iu}(k)$), generalised costs ($c_p^{iu}(k)$) and route logsum values $rls_{rs}^{iu}(k)$. The updated traffic conditions are fed back into the departure time choice model and elastic demand module in the outer loop of the modelling framework. The route logsums are used in the departure time choice model together with the scheduling delay attributes and behavioural parameters to calculate the new dynamic demand $\tilde{D}_{rs}^{iu}(k)$ in outer loop iteration i for each user class u leaving in departure period k from origin r to destination s . Before starting a new outer loop iteration with a new route choice and traffic simulation, the changes in total demand levels need to be applied first using the elastic demand module. This module uses the logsums resulting from the departure time model $rls_{rs}^{iu}(d)$ together with elasticity and car shares as input. A choice model is run in each outer loop iteration, which determines the demand for car trips using a “virtual” other-than-car choice alternative. The utility of the virtual alternative and logit scale parameters can, if they are not present, be calibrated in the first iteration using the elasticity and car share and they are kept constant in future iterations. The demand $\tilde{D}_{rs}^{iu}(k)$ from the departure time choice model is altered using multiplication factors such that the new car dynamic demand $D_{rs}^{iu}(k)$, which includes both departure time choice and elastic demand effects, results. This is the new demand that results from this iteration, but is still not yet the demand that will be used in the next iteration. In order to reach stable equilibrium conditions, the dynamic demands of different iterations are averaged using a method of successive averages (MSA) approach.

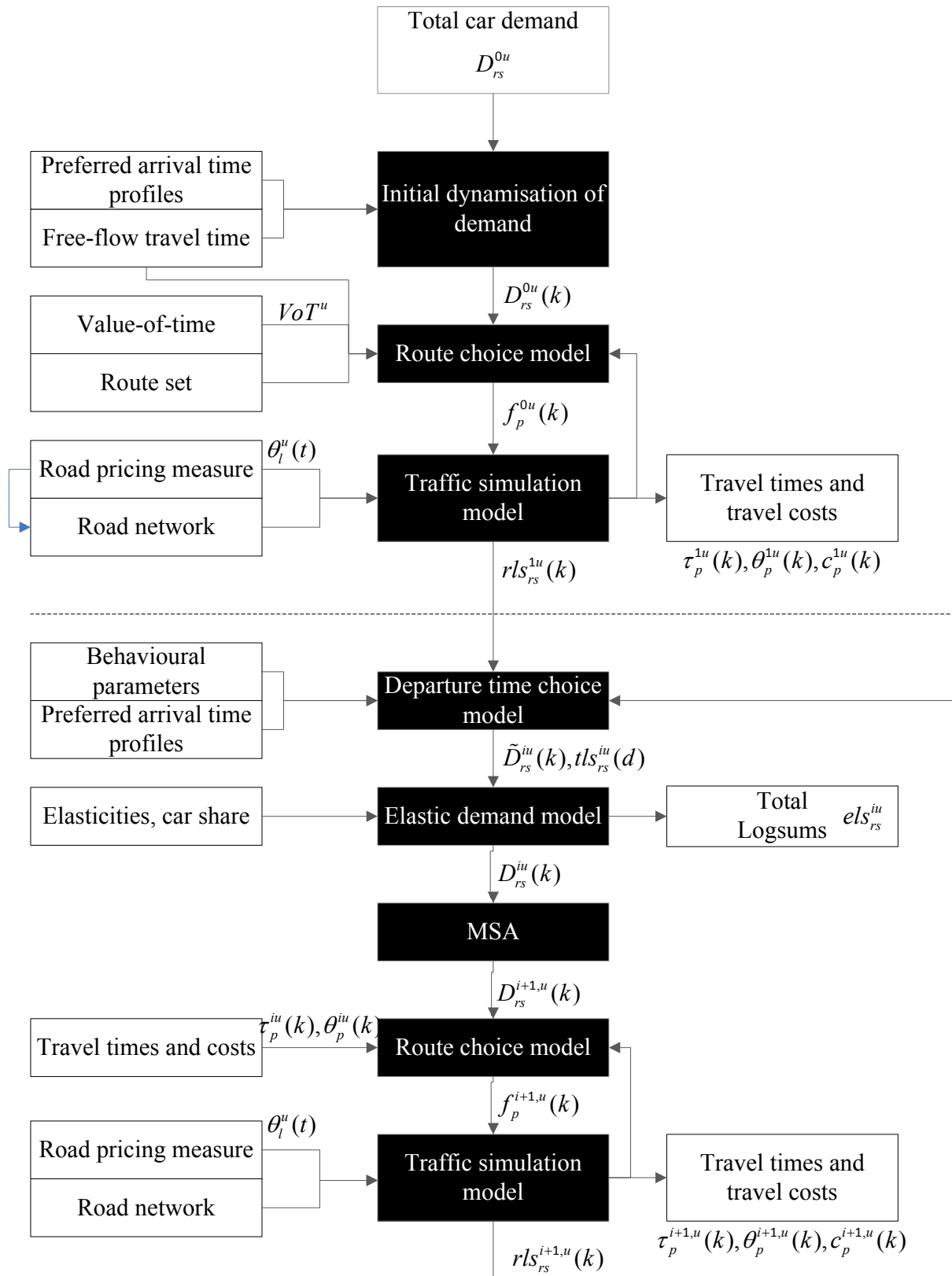


Figure 7.2: Overview of the modelling framework

A last issue is that in order to know the starting traffic conditions for the behavioural models, the iterative procedures need to be initialised. To this end, a first traffic simulation is conducted in which all the traffic (no elastic demand effects yet) leave at the preferred

departure time. This part of the framework is shown above the dotted line. For the inner loop, the initial route choice always starts from the free-flow traffic conditions.

7.4 Dynamic traffic assignment model

In this research, an analytical macroscopic multi-user class dynamic equilibrium for large scale networks was used (see Bliemer (2001), Bliemer et al. (2004)). This DTA model consists of three model components, namely: 1) a route generation model (see Bliemer and Taale (2006) and Zantema et al. (2007)), 2) a route choice model and 3) a dynamic network loading model (DNL). The DTA model considers a wide range of possible *user classes*, categorized into two groups: different *driver classes* and different *vehicle classes*. Different driver classes have different preferences or have different information available, impacting their route choices.

The route choice module models the behaviour of the travellers by choosing the best route for themselves from the set of available routes as determined in the route generation model. The best alternative route depends on the route costs for each of the alternatives and consists mainly of the route travel time, but can include other (non-additive) cost components, such as tolls. The DTA model in the current version is not capable of a simultaneous calculation of departure time choice and route choice.

7.4.1 Route choice model

The route choice model is a logit model based on a route cost function. For each available route between an origin and destination, these route costs are determined. The route cost function in the DTA model can be specified by the modeller, and in this modelling framework the route costs include toll cost and travel time, where a value of time (per user class) is used to determine the generalised costs. For a given departure time, the car drivers are assumed to consider different route alternatives having some attributes and choose their subjective optimal route. The route alternatives available to the car drivers are determined by a pre-trip route generation procedure, in which the most likely route alternatives are generated for each origin-destination (OD) pair (see also Zantema et al. (2007)). Each of these routes is assumed to have a generalized travel cost. This route travel cost is composed of two main components, namely the congested route travel time and a possible additional monetary cost. Mathematically formulated, the following generalised route travel cost function and utility function are used:

$$c_p^u(k) = VoT^u \tau_p^u(k) + \theta_p^u(k), \quad (7.1)$$

$$U_p^u(k) = -c_p^u(k) + \varepsilon_p^u(k) \quad (7.2)$$

where $c_p^u(k)$ is the generalised cost for user class u taking route p when departing at time k , and $U_p^u(k)$ the associated utility. $\tau_p^u(k)$ is the route travel time for route p departing at time k , and $\theta_p^u(k)$ is an additional (monetary) cost on that route. The term $\varepsilon_p^u(k)$ is a random unobserved cost component, which represents all other cost components. The VoT^u is the value-of-time user class u .

Making some assumptions ($\varepsilon_p^u(k)$'s are independently extreme value type I distributed over all routes), the percentage of car drivers choosing route p for departure time k equals (according to the multinomial logit model (see McFadden, 1976):

$$\psi_p^u(k) = \Pr(U_p^u(k) \leq U_{p'}^u(k), \forall p') = \frac{\exp(-\mu_1 V_p^u(k))}{\sum_{p'} \exp(-\mu_1 V_{p'}^u(k))}, \quad (7.3)$$

where μ_1 is a scaling parameter (which is inversely related to the variance of the random unobserved component). Multiplying this percentage by the total number of car drivers from r to s at time k , $D_{rs}^u(k)$, yields the route flows $f_p^u(k)$, that is,

$$f_p^u(k) = \psi_p^u(k) D_{rs}^u(k). \quad (7.4)$$

This dynamic travel demand $D_{rs}^u(k)$, depends on the departure time choices of the travellers.

7.5 Departure time choice module

In Chapter 6, the departure time choice behaviour of commuters was modelled based on data collected using a stated choice experiment. Road pricing was an integral part of the stated choice experiment, the data of which were used for model estimation. The departure time choice models resulting from Chapter 6 can be applied in the modelling framework to evaluate the departure time choice adaptations of travellers given different road pricing measures. Besides travel time and travel costs, which are basic components of transportation models, the utility functions also contain scheduling delay components. There are two important issues with these scheduling delay components: 1) they are based on preferred arrival and departure times, which are data that are not vastly available, and 2) they may contain departure as well as arrival scheduling delay components. Arrival time scheduling delays are especially hard to model, since the arrival times are only known *after* the trip has been completed. Both issues are discussed in more detail in the next sections.

Determining preferred arrival times

Determining preferred arrival time profiles is not a trivial issue. Travel diaries and traffic count data are mostly set up to measure the current behaviour, not the desired behaviour. Although not part of this research, two modelling approaches seem feasible. The first approach uses departure time choice modelling in the base year estimation of the model. In this case, the preferred arrival times can be calibrated such that the resulting base year model validates well towards independent traffic data (volumes, travel times, etc.). This is a difficult process, but feasible, and has been applied for the case study project in the next chapter. The second approach uses a reverse engineering approach, as proposed by Teekamp et al., 2002, where the unknown preferred arrival times are back calculated, based on an equilibrium base year model situation and a departure time choice mode.

Arrival time scheduling delays

Most DTA models assign a certain amount of traffic to the network each discrete time instant. This implies that the departure times of trips are not that difficult to adjust by either increasing or decreasing the amount of traffic assigned to the network. The arrival times of trips, however, are normally the output of the model rather than input. This is the result of the unknown travel conditions on the network, prior to performing the dynamic network loading or traffic simulation. This is no different than the choice situation in reality, where a traveller

can only choose a departure time and, within certain boundaries, can have expectations about their arrival time based on past experiences or information sources.

Since the arrival times are the output of the model rather than the input, determining arrival time scheduling delays requires some assumptions. In the modelling framework, the actual arrival times ($\hat{a}_{rs,i}^u(k)$) for a trip from r to s for user group u , departing in period k in iteration i , are based on the travel times from the previous iteration step ($\bar{\tau}_{rs,i-1}^u(k)$). This travel time is rounded towards the size of demand period intervals.

$$\hat{a}_{rs,i}^u(k) = k + \bar{\tau}_{rs,i-1}^u(k) \quad (7.5)$$

Using this approach the arrival time scheduling delays can be calculated according to Equations (7.6) through (7.9). These arrival time scheduling delays depend on the departure time scheduling delays. With the actual travel times $\bar{\tau}_{rs,i-1}^u(k)$ always being equal or larger than the free-flow travel time $\hat{\tau}_i^u$, an arrival time scheduling delay early $ASDE_{rs,i}^u(k)$ can only be positive when the departure time scheduling early $DSDE_i^u$ is larger than the difference between the actual and free-flow travel time.

$$ASDE_{rs,i}^u(k) = \max \{PAT_i^u - \hat{a}_{rs,i}^u(k), 0\} \quad (7.6)$$

$$ASDE_{rs,i}^u(k) = \max \{ \hat{\tau}_i^u - \bar{\tau}_{rs,i-1}^u(k) + DSDE_i^u, 0 \} \quad (7.7)$$

The arrival scheduling delay late $ASDL_{rs,i}^u(k)$ also depends on the departure time scheduling delays. The departure time scheduling delay early $DSDE_i^u$ and late $DSDL_i^u$ can never both be positive in Equation (7.9). In the situation in which the departure time scheduling delay early is positive, scheduling delay late can be positive if the delay ($\bar{\tau}_{rs,i-1}^u(k) - \hat{\tau}_i^u$) on a trip is larger than the departure time scheduling delay early.

$$ASDL_{rs,i}^u(k) = \max \{ \hat{a}_{rs,i}^u(k) - PAT_i^u, 0 \} \quad (7.8)$$

$$ASDL_{rs,i}^u(k) = \max \{ \bar{\tau}_{rs,i-1}^u(k) - \hat{\tau}_i^u - DSDE_i^u + DSDL_i^u, 0 \} \quad (7.9)$$

In the situation in which the departure time scheduling delay late is positive, there automatically exists an arrival time scheduling delay late, since the actual travel time is always equal or larger than the free-flow travel time. Depending on the amount of delay, the arrival time scheduling delay late may be larger than the departure time scheduling delay late.

7.5.1 Departure time choice model

The departure time module incorporated in the modelling framework is a MNL model, in which the parameter values can be set by the modeller. The total disutility of travelling from r to s when departing at time k while preferring to depart at time d and to arrive at time a , i.e. ($U_{rs}^u(k | d)$), is given by:

$$\begin{aligned} U_{rs}^u(k | d^u) = & rls_{rs}^u(k) + \frac{\beta_{dsde}^u}{\beta_\theta^u} DSDE(k | d^u) + \frac{\beta_{dsdl}^u}{\beta_\theta^u} DSDL(k | d^u) \\ & + \frac{\beta_{asde}^u}{\beta_\theta^u} ASDE(k | a^u) + \frac{\beta_{asdl}^u}{\beta_\theta^u} ASDL(k | a^u) + \varepsilon_{rs}^u(k | d^u) \end{aligned} \quad (7.10)$$

$DSDE(k|d^u)$ is the time that the car driver departs earlier than his/her preferred departure time, when departing at time k , while preferring to depart at time d^u . $DSDL(k|d^u)$ is the time that the car driver departs later than preferred, $ASDE(k|a^u)$ is the time that the car driver arrives earlier than his/her preferred arrival time and $ASDL(k|a^u)$ is the time that the traveller arrives later than his/her preferred arrival time. The term $\varepsilon_{rs}^u(k|d^u)$ is a random unobserved component that represents all other cost components. The parameters β_t^u to β_{asdl}^u are behavioural parameters for different user classes u .

The preferred departure time d^u and preferred arrival time a^u of travellers are related by subtracting the free-flow travel time from the preferred arrival time. So, even if the arrival time profiles for all zones may be assumed equal, the departure time profiles are different for each origin-destination pair. With equal arrival times, long trips will, for example, depart earlier than short trips.

Again assuming that the random components $\varepsilon_{rs}^u(k|d^u)$ are independently extreme value type I distributed over all departure times, the percentage of car drivers (with a preferred departure time) choosing departure time k is given by

$$\varphi_{rs}^u(k|d^u) = \Pr(U_{rs}^u(k|d^u) \leq U_{rs}^u(k'|d^u), \forall k') = \frac{\exp(-\mu_2 U_{rs}^u(k|d^u))}{\sum_{k'} \exp(-\mu_2 U_{rs}^u(k'|d^u))}, \quad (7.11)$$

where μ_2 is a scaling parameter. Multiplying this percentage by the total number of car drivers preferring to depart at time d^u , i.e. $\hat{D}_{rs}^u(d^u)$, yields the total number of drivers of user class u that will actually depart at time k : $\tilde{D}_{rs}^u(k)$. Summing over all preferred arrival times, the total number of car drivers departing at time k , is given by:

$$\tilde{D}_{rs}^u(k) = \sum_{d^u} \varphi_{rs}^u(k|d^u) \hat{D}_{rs}^u(d^u) \quad (7.12)$$

7.6 Elastic demand

In the modelling framework, the departure time choice and route choice are included as explicit choice processes. Departure time choice and route choice together distributed the travel demand in time and space, while the total demand is kept constant. Ideally, the model framework would explicitly model the effects of road pricing using different travel choice models such as trip generation, trip distribution and mode choice. Since the focus of the research is to determine the departure time and route changes of time-varying road pricing measures, an elastic demand module was added to the modelling framework that takes into account those changes in travel demand as a result of behavioural responses to road pricing. In the elastic demand module, changes in departure time logsums for each user class and OD-pair ($tls_{rs}^{iu}(d)$) will lead to changes in demand by application of a choice model where travellers choose between car and a virtual alternative mode. The utility functions of the car and the virtual other alternative are given by Equations (7.13) and (7.14).

$$U_{rs}^u(car) = \sum_d t l s_{rs}^u(d) + \varepsilon_{rs}^u \quad (7.13)$$

$$U_{rs}^u(other) = V_{rs}^u + \varepsilon_{rs}^u \quad (7.14)$$

The V_{rs}^u of the alternative mode needs to be calibrated together with the scale parameters of the logit function, such that the model reproduces the desired levels of car demand and desired elasticity. In the modelling framework, an iterative procedure is included that calibrates these values when the reference car share and elasticity are given. The probability of choosing to travel by car is given by Equation (7.15):

$$\zeta_{rs}^u(car) = \Pr(U_{rs}^u(car) \leq U_{rs}^u(other)) = \frac{\exp(-\mu_3 U_{rs}^u(car))}{\sum_m \exp(-\mu_3 U_{rs}^u(m))} \quad (7.15)$$

By assuming first that $\mu_3 = 1$, the $U_{rs}^u(other)$ can be determined when $\zeta_{rs}^u(car)$ is given. The $U_{rs}^u(car)$ is then increased by, for example, 10%, and when the elasticity is known, the μ_3 can be estimated in an iterative process. Equation (7.15) is also used to include the elastic demand effects in the new demand $D_{rs}^u(k)$ as the new dynamic car demand that results from the departure time choice model ($\tilde{D}_{rs}^u(k)$) is multiplied by the quotient of $\zeta_{rs}^u(car)$ and the reference car share ($P_{ref}(car)$), see Equation (7.16).

$$D_{rs}^u(k) = \frac{\zeta_{rs}^u(car)}{P_{ref}(car)} \tilde{D}_{rs}^u(k) \quad (7.16)$$

7.7 Conclusions

In this chapter, we developed a practically applicable modelling framework capable of assessing the network effects of time-varying road pricing measures. In order to do this, it is necessary to use a dynamic traffic simulation or assignment model, since only those models are capable of representing the changing traffic conditions over time. Route choice and departure time choice were included in the modelling framework as explicit choice models, while an elastic demand model was used to determine the changes in demand levels in a more simplistic manner.

The modelling framework that results from this chapter is one of the few dynamic modelling frameworks that exist which can forecast the effects of time-varying road pricing on route, departure time and demand levels for different user classes. The modelling framework was applied in different research projects to assess the network effects of different road pricing measures (see Tillema (2007); Bliemer and Van Amelsfort (2008) and Zantema et al. (2008)). The modelling framework was also applied in a road pricing optimisation study (see Brands et al. (2008)).

The setup of the framework is flexible so that the different components can be changed in different applications. The elastic demand module may, for example, be replaced by a sequence of mode, destination and trip frequency models. Another interesting future development of the framework might be to consider simultaneous route and departure time

choice, to incorporate more complex discrete choice model forms for route and departure time choice or to extend the dynamic traffic assignment model so that it is capable of handling flow-dependent road pricing measures.

In the next chapter, we will first test the modelling framework on a small simplified network around the city of Delft. In Chapter 9, we will then present one of the case studies in which the modelling framework was applied to assess the network effects of a reward scheme under which participants of the pilot project “Spitsmijden” received monetary incentives if they did not travel during the morning peak.

8 Test case: simplified Delft network

In this chapter, the test results of the overall framework and the specific components of the modelling framework are presented. The departure time choice model, which is an important component of the modelling framework, is also tested using the different specifications of scheduling delay components for similar models as presented in Chapter 5 of part B.

The purpose of the chapter is twofold. The first purpose is to show that the modelling framework works correctly. The second purpose is to show the effects of different departure time choice model specifications on traffic network performance.

For each of the model components, specific tests are constructed with hypotheses about the expected outcomes of the model. In each of the tests, a reference case without road pricing is compared to a case with road pricing where specific behavioural responses should be predicted depending on the specific road pricing measure. The road pricing measures vary in level of differentiation by location, time and user class. The modelled effects of road pricing are then compared on a route, matrix and network level.

The test results in this chapter demonstrate that the different scheduling delay specifications in the departure time choice models have a significant impact on the traffic network performance. A choice model based only on departure time scheduling components leads to more and larger shifts in departure time than a model based on arrival time scheduling or a combined scheduling delay approach.

The outline of this chapter is as follows. First, the setup of the test case model is described. In Section 8.2, the tests for each of the model components are determined and hypotheses are formulated about expected model results. In the succeeding sections, the route choice, departure time choice and elastic demand module test results are discussed.

8.1 Test case model description

The case study represents the road network of the city of Delft. This city is located in the western part of the Netherlands, and it lies between two major cities: Rotterdam and The Hague. Figure 8.1 shows this road network. Delft is surrounded by two motorways, the A13 on the Eastside and the A4 on the Westside. The A4 ends in the south of Delft, but is supposed to be extended in the future. In the north, the A4 and A13 join around Rijswijk. Delft has a historic centre with small streets and waterways. The road network there does not allow for through traffic. Around the city centre, there are larger roads, which form a network to get around Delft and connect to the larger provincial road and motorways. There is an important north-south provincial road between the A4 and A13 (Provincialeweg) and an important east-west provincial road connecting the A4 and A13.



Figure 8.1 : the road network around Delft

In the simplified model network, only the two motorways and two provincial roads are included. Figure 8.2 shows how the study area is simplified and modelled. The study area is differentiated into rural and urban areas. A13, A4 and the N470 represent the rural area, while the provincial road of Delft represents the urban areas. The impacts of road pricing are studied within the borders of the study area shown in Figure 8.2. The network consists of 137 links and 90 nodes.

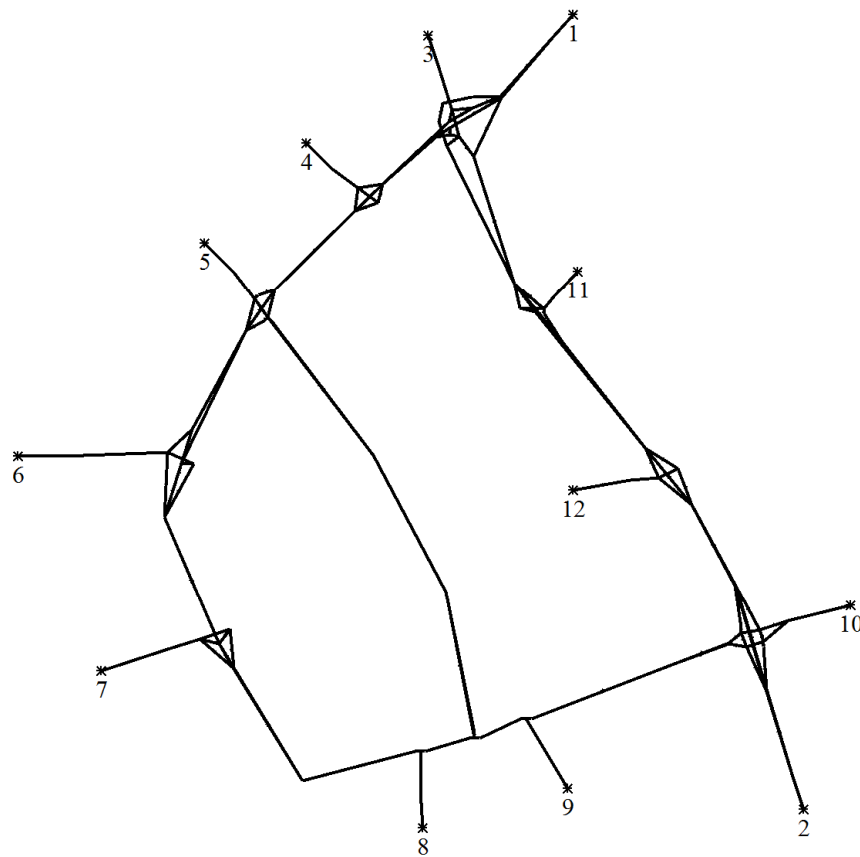


Figure 8.2 : The simplified network (study area)

The study area is divided into 12 zones of trip origins and destinations. These zones represent the different agglomerations in and around Delft. Different road types are connecting these zones. The characteristics of these roads are given in Table 8.1.

Table 8.1 : Road types and their characteristics

	user class	speed limit	capacity	speed at capacity
Motorway	car	120	6000	80
	freight	85	6000	70
Dual carriageway	car	100	2200	75
	freight	85	2200	65
Provincial road	car	80	2100	65
	freight	70	2100	60
Urban road	car	50	2000	45
	freight	50	2000	40

In the test case, two user classes are distinguished, namely: car and freight. Cars and freight use different networks, as they are allowed to drive with different speeds. Cars and freight also differ in values of time for route choice, have different parameters in the departure time choice model, have different trip elasticity and have different toll levels. The total demand, in the reference situation, contains 31,499 trips for cars and 7,874 trips for freight. With elastic demand, these trip totals may change.

These different model runs will be examined using aggregated network statistics such as total travel time spent, total vehicle miles travelled and total revenues collected. The convergence of the model framework is examined. Since there are limited routes available in the network (for every OD-pair, there are no more than three logical routes), it is also possible to analyse the results for individual OD-pairs in terms of changing demand, departure times, route choice and traffic conditions.

8.1.1 Model inputs

In order for the model to run, different parameters must be set. In order to get comparable results, these parameters (see Table 8.2) are kept constant in the model runs. In the test case, we want to examine when an equilibrium situation has been reached. For this purpose, we use a large number of outer loop (40) and route choice iterations (10). This implies that the traffic is simulated through the network 400 times.

Table 8.2 : Global parameter settings

Global parameters	Value
Simulation period	6:00 – 10:00 a.m.
Demand period (departure time choice period)	10 minutes
Output aggregation time step	5 minutes
Internal time step (INDY traffic simulation)	3 seconds
route iterations (path generation parameter)	40
route overlap (path generation parameter)	0.9
route choice spread (route choice stochasticity parameter)	0.07
departure time choice mu (MNL scale factor for departure time choice)	2

In the test case, a demand period of 10 minutes is used. It is important that the different departure periods are distinct enough for good departure time choice. This means that the period must not be too small (not many changes in a minute) and not too big (all difference gets averaged out). The output time step of 5 minutes is somewhat more trivial, as it sets the frequency at which link output is saved for later analyses. A higher frequency (lower step) gives more detailed results and includes less averaging of results, but it takes up more hard disk space and memory.

The internal time step for the traffic simulation is set equal to the smallest free-flow travel time on a link in the network (3 s). The higher the internal time step, the shorter the calculation times. Higher time steps do lead to less accurate results and underestimation of route travel times.

Between all origins and destinations, 184 routes in total were calculated for 125 OD-pairs using a Monte Carlo simulation approach to introduce variation in link travel times. This variation is increased automatically with each iteration (40 in total). If a new route overlaps with an existing route for more than 90 percent (overlap parameter), it is disregarded and is not added to the route set.

In the route choice of the model, the route choice spread parameter is set to 0.07 to influence the stochasticity of the route choice model. The same type of parameter is used for the departure time choice model, and this is set to 4 in the test case.

Preferred arrival time profiles

At the centre of the departure time rescheduling model are the preferred arrival time profiles for each zone and for each user class. The scheduling delay components in the utility function are based on deviations from the preferred arrival time and/or the preferred departure time. In this test case, the preferred arrival time profile, as shown in Figure 8.3, is identical for each zone. If data are available, this can easily be adjusted.

The preferred arrival time profile in the test case model has a peak at 8:30 a.m., a normal work start time in the Netherlands. In the test case, car and freight share the same preferred arrival time profile.

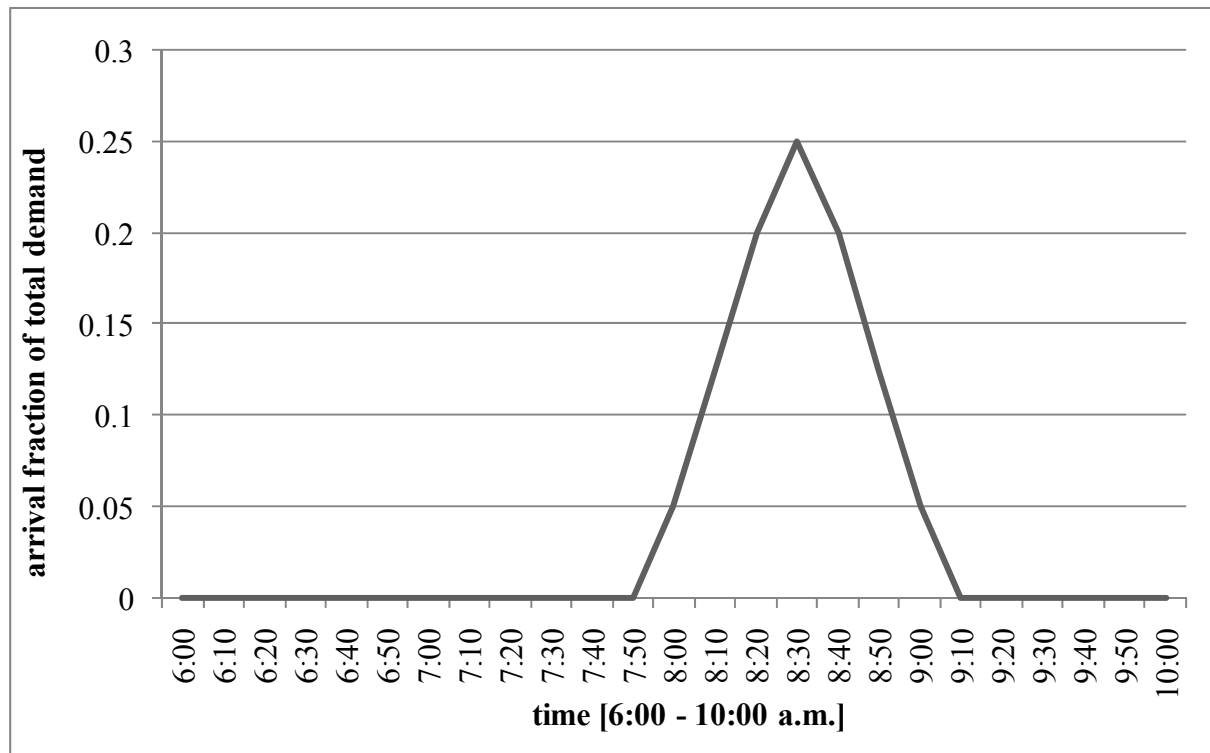


Figure 8.3: Preferred arrival time profiles car and freight

Similarly to the approach presented in chapter 5, the preferred departure times are estimated by subtraction of the free-flow travel times from the preferred arrival time.

User class dependent model parameters

For each of the user classes, different model parameters can be set. The route choice is influenced by the value-of-time of each user class. Also, the PCU-value of each user class can be set. Although it would be normal to differentiate this parameter between cars and freight, this difference is neglected in this test case, assuming that the demand matrices are already PCU based. In the test case, a value-of-time of €12.- per hour is used for cars and €35.- per hour for freight. These values somewhat resemble the values found in the Netherlands.

The departure time choice model currently included in the framework allows for six parameters to be set for the utility function specification. In the test case, the parameter values are set as shown in Table 8.3. These values are, for cars, based on choice models similar to those estimated in Chapter 5, while for freight only the cost parameter is adjusted such that the implied value-of-time of the model is equal to €35.- per hour.

Table 8.3 : parameter values for departure time choice model

variable	car	freight
cost	-0.1158	-0.0422
travel time	-0.0247	-0.0247
ASDE	-0.0292	-0.0292
ASDL	-0.0339	-0.0339
DSDE	-0.0162	-0.0162
DSDL	-0.0791	-0.0791

The elastic demand parameters in the test case are set to -0.3 for cars and -0.3 for freight, and the reference shares were set to 0.85 for both modes.

8.2 Tests and expected results

To investigate the performance of the model framework, the model framework is applied in a test case on different road pricing tests. Analyses and comparisons of the test should demonstrate that each of the model components works correctly with road pricing measures in place. Three components of the model framework are evaluated in this chapter: 1) the route choice module; 2) departure time choice module; 3) elastic demand module.

Route choice test

In order to determine if the route choice works properly, the model is applied without departure time choice and elastic demand. To achieve this, only one outer loop iteration is used, which means that all traffic departs at the preferred departure time. To identify the effects of toll on route choice, two model runs are conducted: 1) a reference test without toll and 2) a test with toll. In the toll test, a toll (€ 5) is levied for cars on the A13 motorway in the north-bound direction. The high toll should push most of the cars from the A13, while the freight may return to the A13 as a result of its improved travel times and the deteriorated conditions on alternative routes.

Departure time choice test

In this test, route choice and elastic demand are turned off. A single route choice iteration within INDY is used to minimize the route choice in this test. However, even in the initial route choice, toll costs will be included. In order to make sure that travel time is the only factor of importance in the route choice, the toll per kilometre is set equally on all links and an extremely high value-of-time (€1,000.- per hour) is used for both car and freight. Again, two model runs are conducted to determine the departure time choice effect of the kilometre charge: 1) a reference test without the charge and 2) a toll test with the charge. The tolls are differentiated over time. Also, tolls will be applied such that cars are pushed to times before the peak and freight to times after the peak.

Elastic demand test

The elastic demand is tested by turning off route choice and departure time choice. Route choice is again manipulated to remain constant as in the departure time choice test. High tolls will be set for cars, while no tolls are charged for freight. Higher elasticity (-0.3) will be used for both cars and freight. As a result, the model should show a decrease in demand for car traffic. The decrease in car demand leads to improvements in the travel times in the network, which might lead to an increase in freight traffic.

8.3 Route choice test

In the route choice test, a toll of 5 euro is in place in the north-bound direction on the A13 motorway. As a result of the toll, much of the traffic on the A13 will divert to the route using the Provincial road parallel to the A13. Note that the route choice changes are dependent on the availability of alternative routes, and the route generation process is therefore important. As shown in Figure 8.4, there is only one alternative route in the model between origin 2 and destination 1. Between origin 12 and destination 11 there is only one route available.

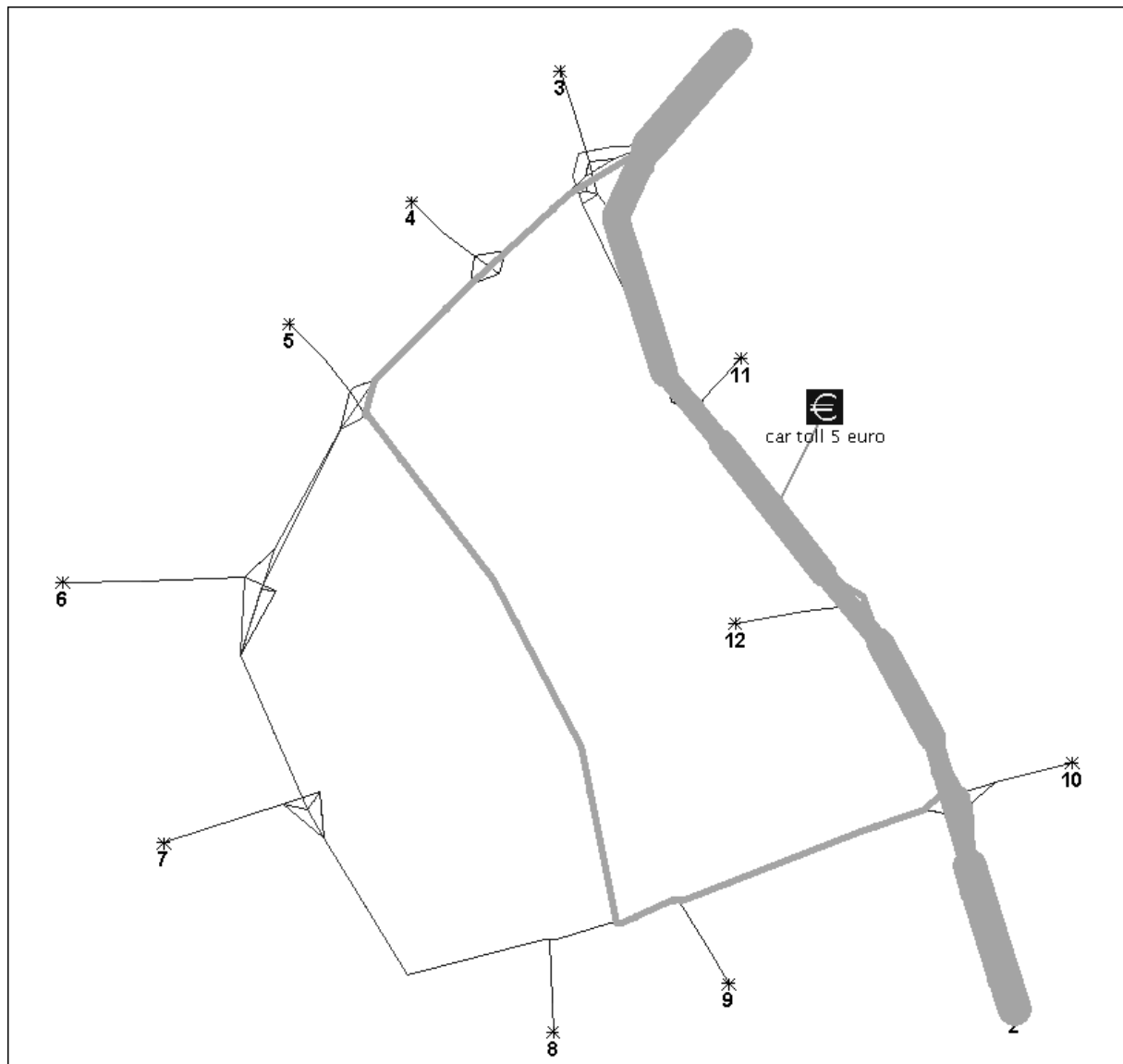


Figure 8.4 : Available routes between origin 2 and destination 1

As a result of the toll on the A13, the traffic flows in the north-bound direction on the A13 are 38% lower (see Figure 8.5), while on the Provincialeweg, volumes increase by 135%. For freight, the reverse effect occurs, as expected. In the north-bound direction on the A13, the freight volumes increase by 18% (see Figure 8.6), while on the Provincialeweg freight volumes are 68% lower.

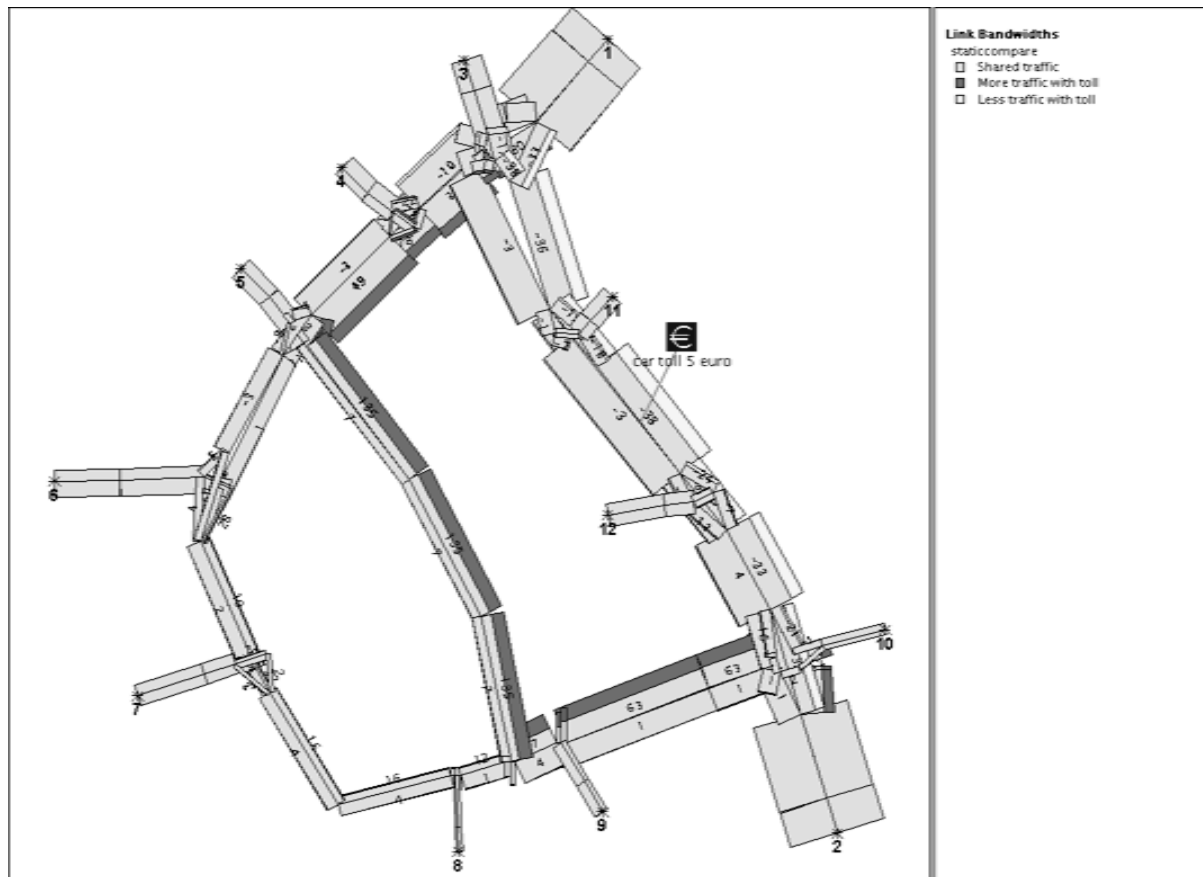


Figure 8.5 : Effect of toll on route choice for cars

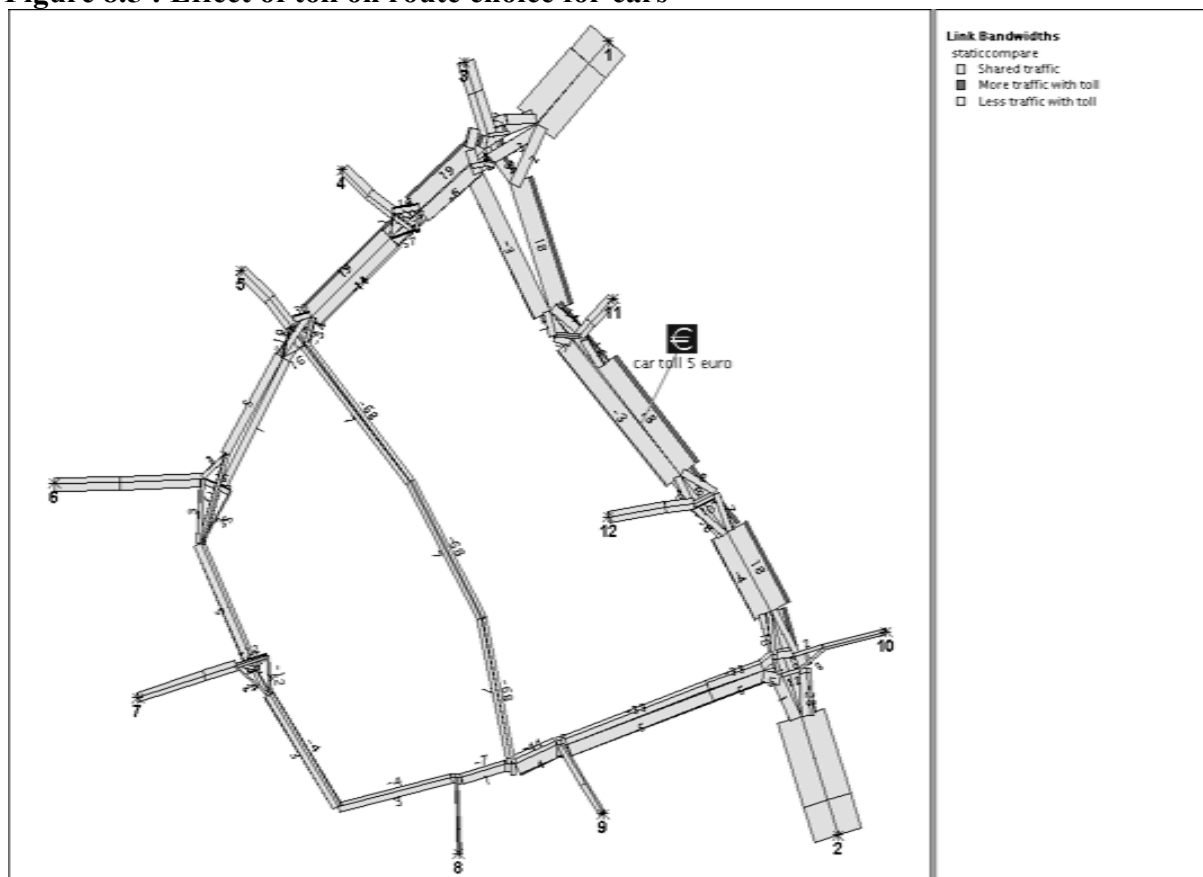


Figure 8.6 : Effect of toll for cars on route choice for freight

8.4 Departure time choice test

In the departure time choice test, a kilometre charge was introduced on all links in the network. The charge was differentiated over time in a simple manner (see Figure 8.7) in order to push car traffic to periods before 7:30 and to push freight traffic to travel after 8:30. This charge differentiation and the levels are chosen solely for testing purposes and may have no meaning in reality. The kilometre charge was set to €0.90 for freight and €0.30 for cars in the charged periods. The freight charge is set higher both because of freight traffic's higher value-of-time and because, considering the scheduling choice parameters, departing later than preferred incurs a higher disutility, which therefore requires a higher toll.

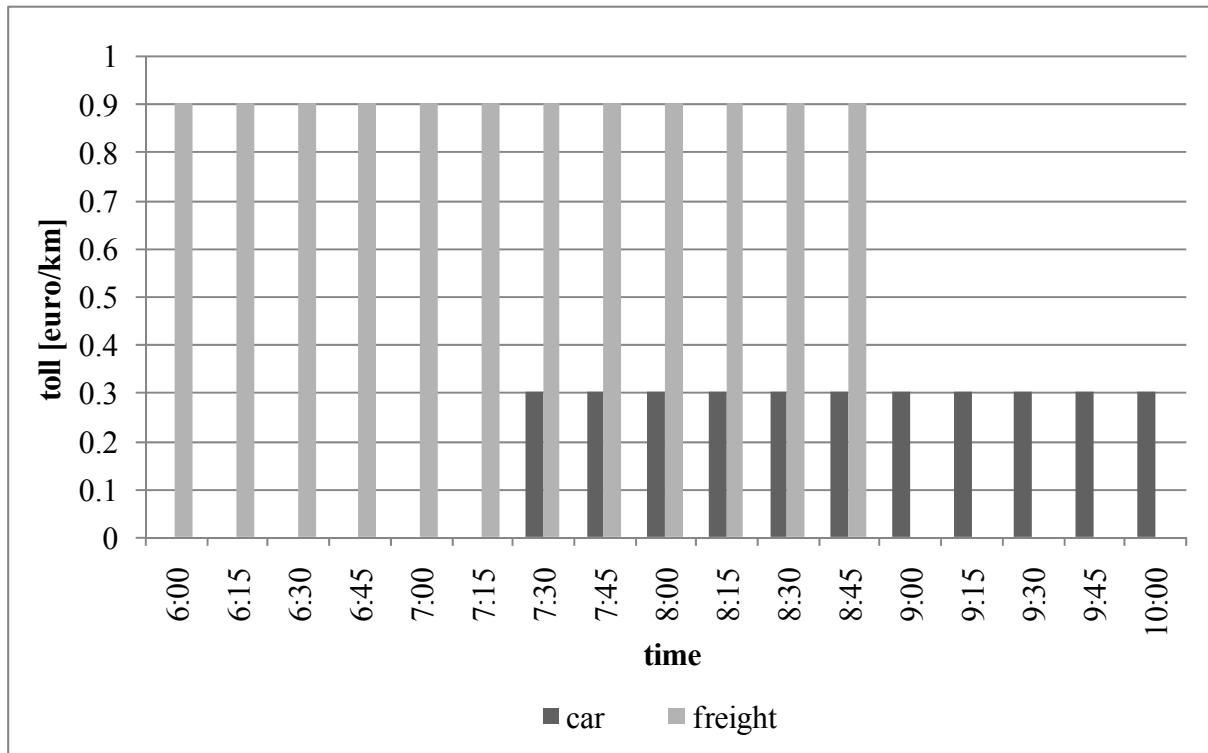


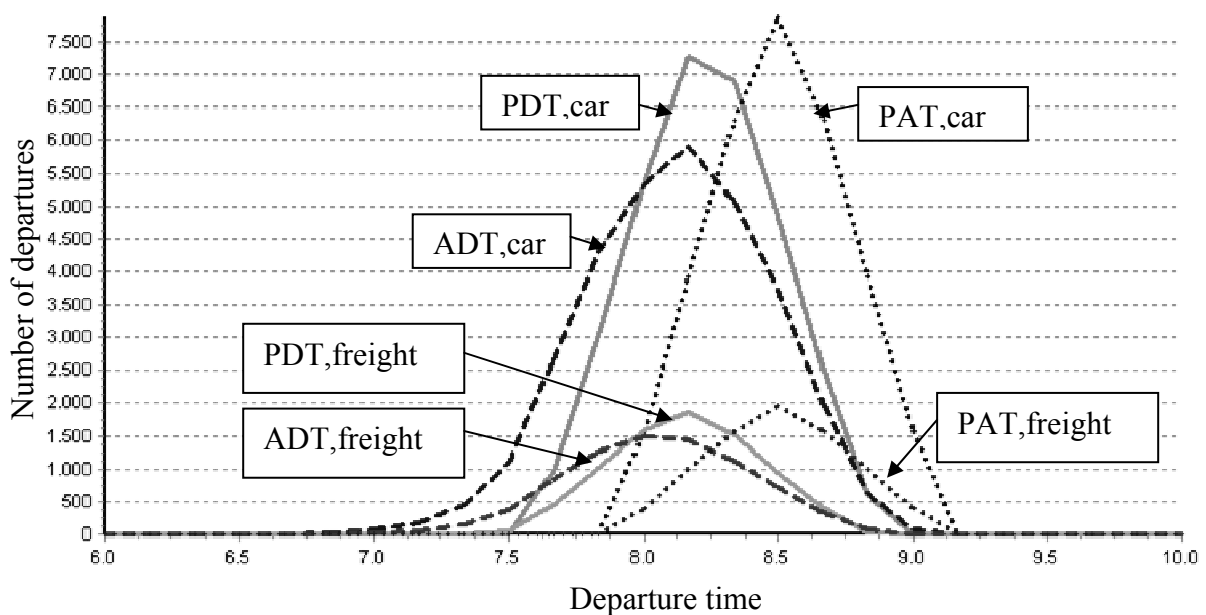
Figure 8.7 : Toll schedule for departure time choice test

In Table 8.4, some network indicators for the test with toll are compared to the reference case without toll. It appears that the route choice was not entirely constant. The mean trip distance and total distance travelled on the network change between the toll and reference case. The difference is about 1promille for both car and freight. These differences are considered to be small enough to draw conclusions about the changes in departure time choice between the reference and toll situation. The changes in mean travel time from Table 8.1 show that the traffic conditions improve for car users, but deteriorate for freight.

Table 8.4 : Network indicators for departure time choice test

	Reference	Toll
Network indicators for car		
The total travel time spent on the network [hours]	10658	10088
Total distance travelled on the network [km]	662289	663465
Mean speed in the network [km/hour]	62.14	65.76
Mean travel time in the network [tt/vehicle]	20.30	19.22
Mean trip distance in the network [distance/vehicles]	21.03	21.06
Network indicators for freight		
The total travel time spent on the network [hours]	2989	3302
Total distance travelled on the network [km]	165316	165266
Mean speed in the network [km/hour]	55.30	50.05
Mean travel time in the network [tt/vehicle]	22.78	25.16
Mean trip distance in the network [distance/vehicles]	20.99	20.99

Figure 8.8 shows the matrix totals of the dynamic demand matrices for both car and freight after the application of toll. For reference, the preferred arrival time profiles are plotted as well. On the horizontal axis are the departure times, and on the vertical axis are the total departures in a 10 minute demand interval. Figure 8.9 shows that, indeed, a large portion of car demand shifts to a departure before 7:30 to avoid paying the toll. Similarly, the freight demand shifts towards a departure time as shortly as possible after 8:30 a.m., to avoid paying the toll.

**Figure 8.8: Dynamic matrix totals for car and freight without toll**

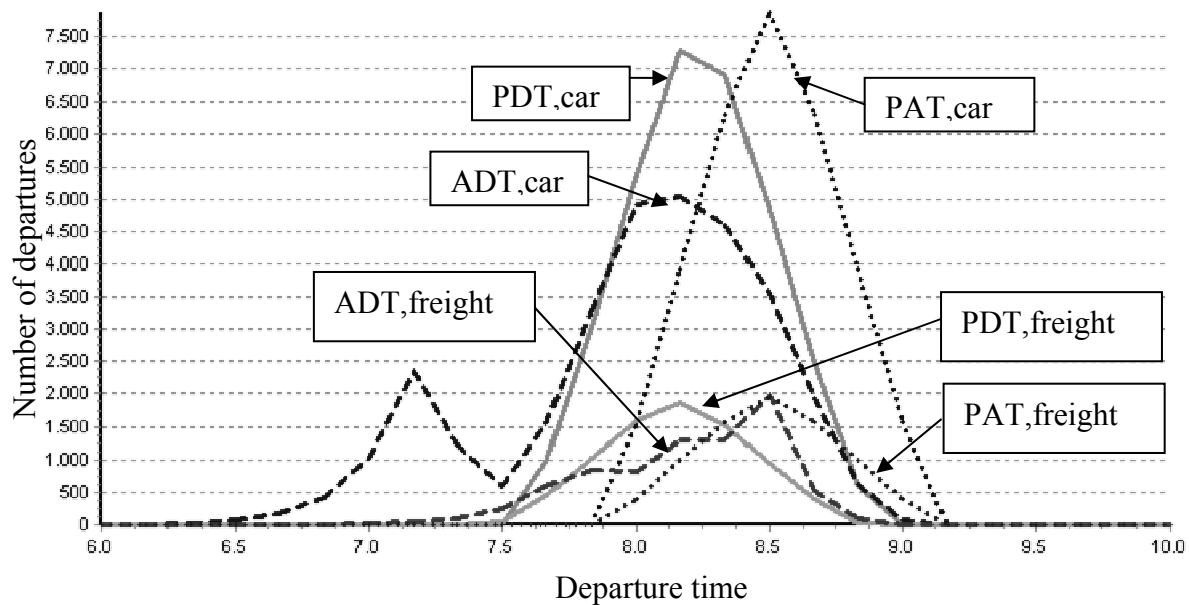


Figure 8.9 : Dynamic matrix totals for car and freight with toll

The departure time adjustments are not equal for all the OD-pairs in the model. For different OD-pairs, the changes in traffic conditions are different when changes in departure time occur. Also, the preferred (and thus actual) departure times of specific OD-pairs are not equal because of different free-flow travel times. Figure 8.10 shows the differences in departure time choice for OD-pair [3,2], where large changes in departure time occur. The car demand changes from a single peak to a dual peak profile. For freight demand, similar changes are visible. Figure 8.11 shows the changes in departure time choice for OD-pair [4,7]. In this case, the departure time changes for car are relatively small, while still larger departure time shifts are shown for freight.

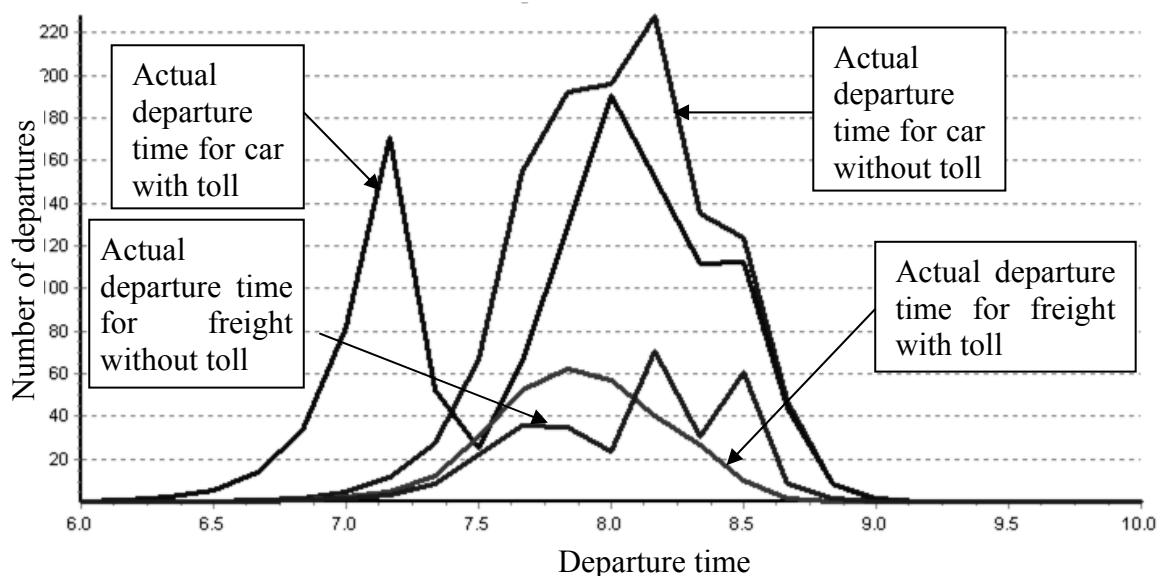


Figure 8.10 : Departure time changes between origin 3 and destination 2

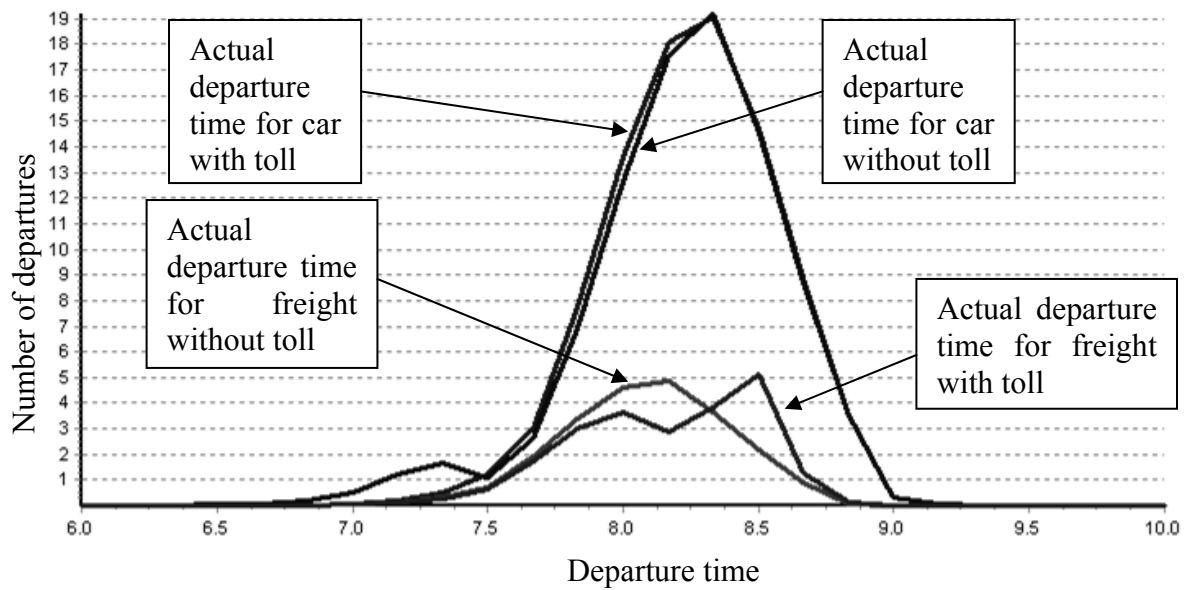


Figure 8.11 : Departure time changes between origin 4 and destination 7

8.5 Elastic demand test

In the elastic demand test, a kilometre charge of €0.60 was introduced for the car mode, while the freight mode remains free of a kilometre charge. For both car and freight, a price elasticity of -0.3 was used. The application of elastic demand results in an overall decrease in car demand, in this case of 37.2%, while for freight an increase in demand of 2.2% resulted. Figure 8.12 shows how the total number of trips for car and freight change per iteration. This total number of trips stabilises rather quickly, and Figure 8.13 shows that the relative changes in the total number of trips changes only by about 0.6% between iteration 9 and 10.

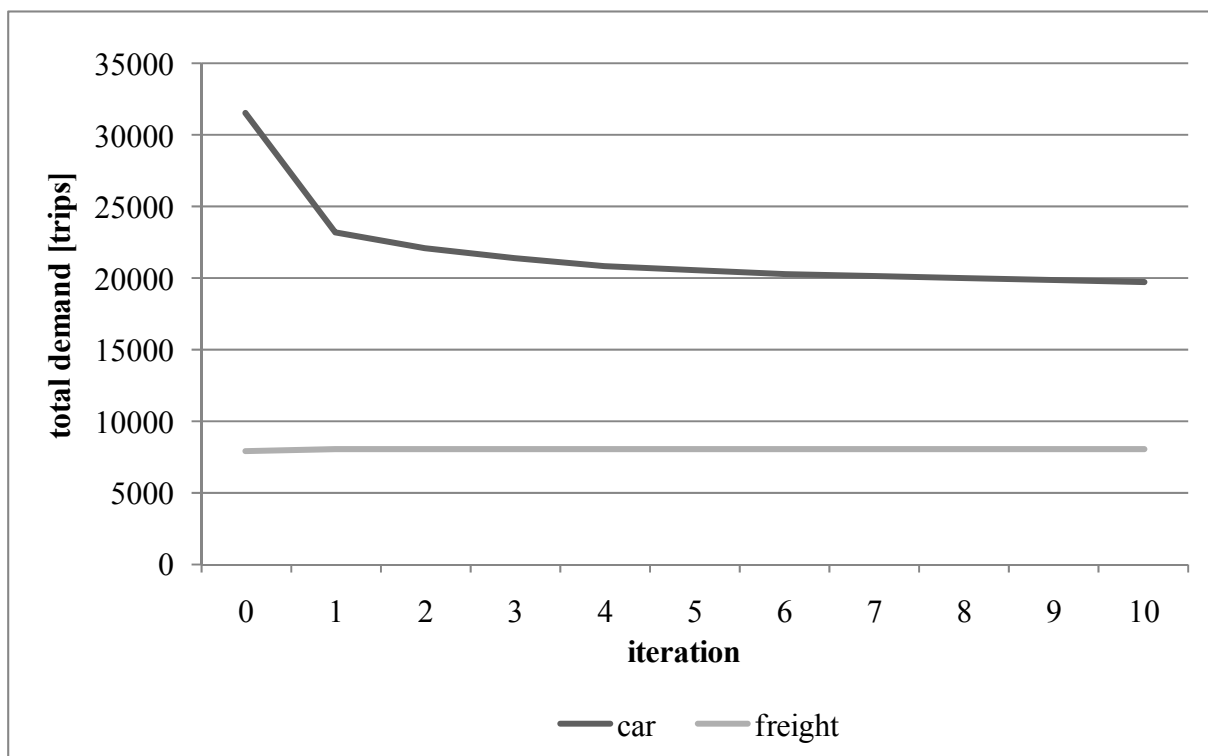


Figure 8.12 : Effect of elastic demand on the total number of trips for car and freight

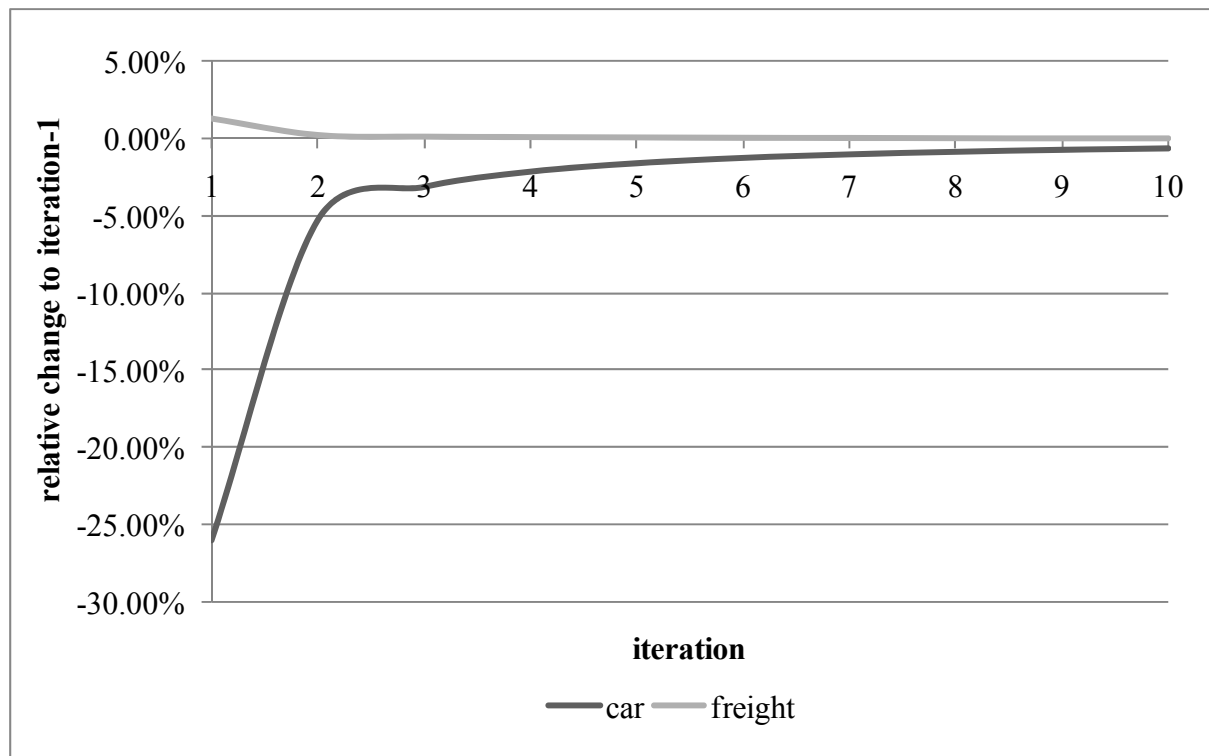


Figure 8.13 : Relative effect of elastic demand on the total number of trips for car and freight

Table 8.5 shows the network indicators for the different model runs. The mean travel time in the network decreases with elastic demand. The mean trip distance is lower for car demand and higher for freight when elastic demand is applied. This is not a result of route choice, since it is turned off, but a result of a larger relative reduction in car demand for longer trips than for shorter trips. For freight the opposite occurs.

Table 8.5: Network indicators for elastic demand model run

Network indicators presented for variant	reference	elastic demand
Network indicators for car		
The total travel time spent on the network [hours]	12011	6873
Total distance travelled on the network [km]	661354	409666
Total number of vehicles put on the network	31499	19783
Mean speed in the network [km/hour]	55.06	59.60
Mean travel time in the network [tt/vehicle]	22.88	20.85
Mean trip distance in the network [distance/vehicles]	21.00	20.71
Network indicators for freight		
The total travel time spent on the network [hours]	3282	3123
Total distance travelled on the network [km]	165085	169068
Total number of vehicles put on the network	7874	8050
Mean speed in the network [km/hour]	50.29	54.12
Mean travel time in the network [tt/vehicle]	25.01	23.28
Mean trip distance in the network [distance/vehicles]	20.96	21.00

8.6 Network effects of differences between departure time models

In Chapter 6, different specifications of scheduling of trips were examined. It was found that both departure time and arrival time rescheduling are significant simultaneously, and that a rather large penalty is associated with departing later than preferred. In this section, the network effects of the different scheduling specifications are examined. Three situations are evaluated and compared: 1) only departure time rescheduling, 2) only arrival time rescheduling and 3) a combined departure time and arrival time rescheduling. All the choice models used in these DTA model runs are similar to those presented in Chapter 6.

8.6.1 Departure time scheduling delays

The departure time scheduling delays are calculated as the deviation of the actual departure time from the preferred departure time, as shown in Equation (8.1). The complete utility function is then given by Equation (8.2). Besides the scheduling delay components, the utility function contains travel cost (toll) $\beta_\theta^u \theta_{ai}^u$ and travel time $\beta_\tau^u \tau_{ai}^u$ components.

$$U_{ai}^u = \beta_\theta^u \theta_{ai}^u + \beta_\tau^u \tau_{ai}^u + \beta_{dsde}^u DSDE_{ai}^u + \beta_{dsdl}^u DSDL_{ai}^u + \varepsilon_{ai}^u \quad (8.1)$$

$$DSDE_{ai}^u = \max \{PDT_i^u - t_{ai}^u, 0\}, \quad DSDL_{ai}^u = \max \{t_{ai}^u - PDT_i^u, 0\}. \quad (8.2)$$

Based on the estimations of choice models presented in Chapter 5, parameter values are used as presented in Table 8.6.

Table 8.6: parameter values used for departure time scheduling

variable	parameter	car	freight
Charge	β_θ^u	-0.1289	-0.0358
Travel time	β_τ^u	-0.0209	-0.0209
DSDE	β_{dsde}^u	-0.0083	-0.0083
DSDL	β_{dsdl}^u	-0.1166	-0.1166

The parameter value for *DSDE* is much smaller than the parameter value for travel time. This means that travellers will prefer to depart earlier rather than facing extra travel time. The result of applying these parameter values in the DTA-model run is that there will be large shifts of travellers to earlier departure times in order to avoid long travel times. This is shown in Figure 8.14 and Figure 8.15, where the actual departure time, the preferred departure time and the arrival time profiles for the matrix totals are plotted for each time interval. These figures also show that, as a result of the high parameter values for *DSDL*, on a matrix total level, no travellers shift to later departure times.

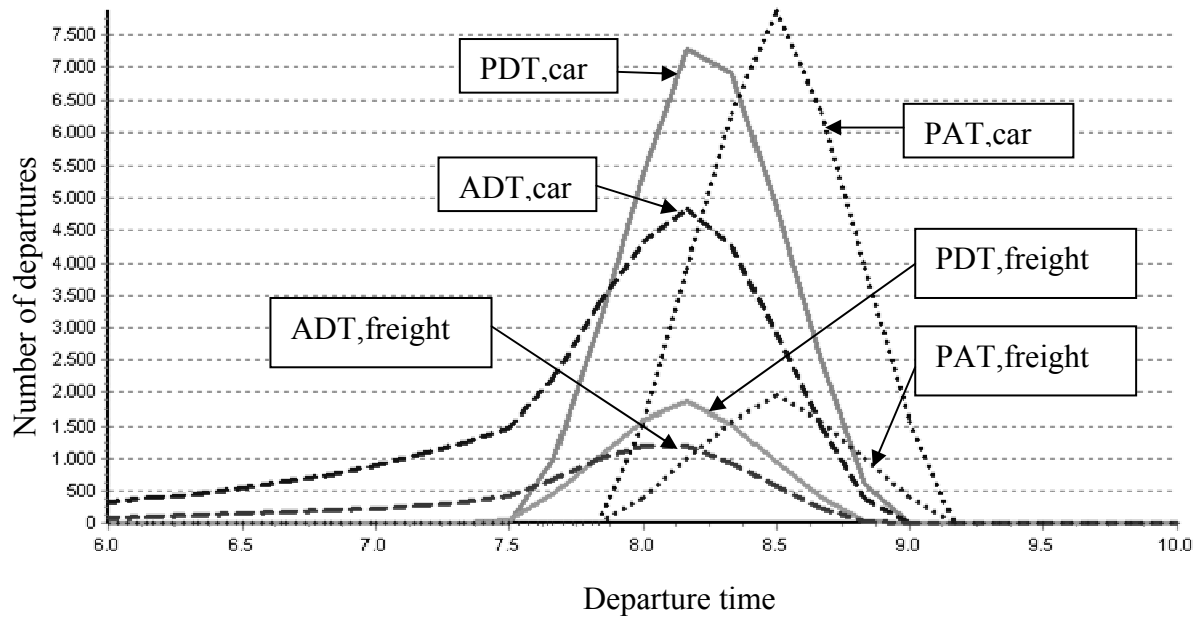


Figure 8.14: Actual departure time and preferred departure and arrival times using departure time scheduling delays [iteration 1]

Figure 8.14 and Figure 8.15 also show a significant difference in the actual departure time profile after 1 and 30 iterations. Although the demand stabilises over iterations, in the first iterations, demand tends to depart earlier than preferred upon each iteration.

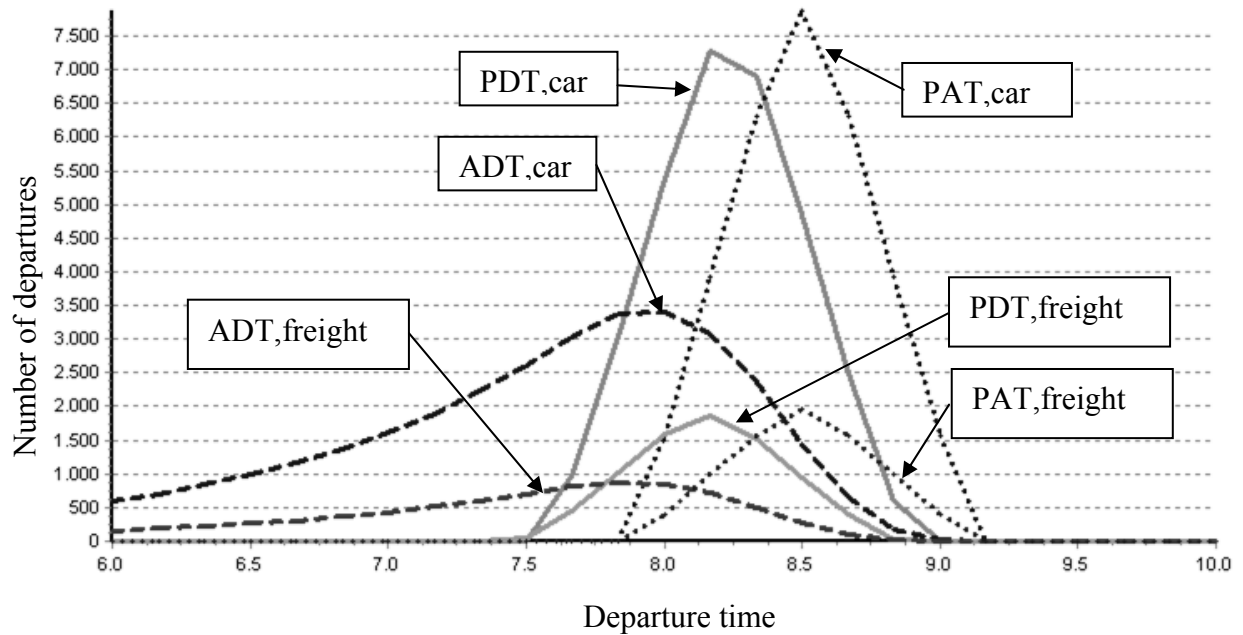


Figure 8.15: Actual departure time and preferred departure and arrival times using departure time scheduling delays [after 30 iterations]

8.6.2 Arrival time scheduling delays

The second model run uses a utility function with scheduling based on the arrival time of a trip. The parameter values are presented in Table 8.7.

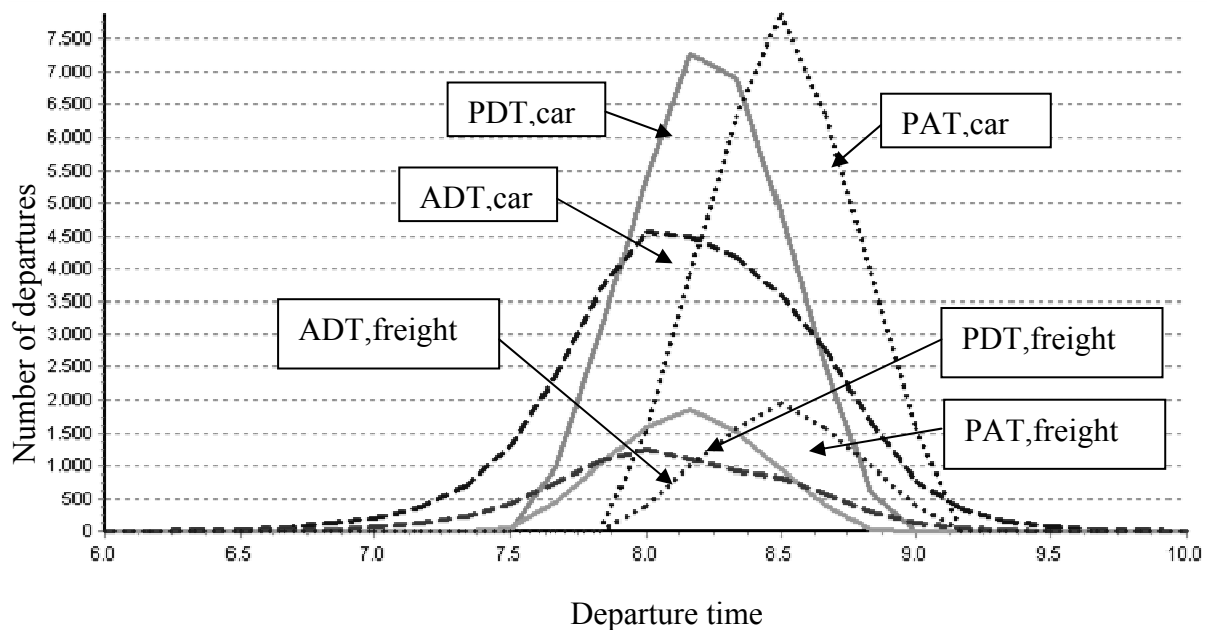
$$ASDE_{ai}^u = \max \{PAT_i^u - t_{ai}^u, 0\}, \quad ASDI_{ai}^u = \max \{t_{ai}^u - PAT_i^u, 0\}. \quad (8.3)$$

$$U_{ai}^u = \beta_{\theta}^u \theta_{ai}^u + \beta_{\tau}^u \tau_{ai}^u + \beta_{adse}^u ASDE_{ai}^u + \beta_{asdl}^u ASDL_{ai}^u + \varepsilon_{ai}^u, \quad (8.4)$$

Table 8.7: parameter values for arrival time scheduling

variable	parameter	car	freight
Charge	β_{θ}^u	-0.1119	-0.0406
Travel time	β_{τ}^u	-0.0237	-0.0237
ASDE	β_{adse}^u	-0.0307	-0.0307
ASDL	β_{asdl}^u	-0.0402	-0.0402

Figure 8.16 shows the resulting actual departure profiles for car and freight after 30 iterations, together with the preferred departure and arrival time profiles. As with the departure time scheduling, the demand tends to move away from the preferred departure time as a result of congestion.

**Figure 8.16: Actual departure time and preferred departure and arrival times using arrival time scheduling delays [after 30 iterations]**

In this case, however, demand is also shifted to periods later than preferred and the shifts are smaller than with departure time scheduling delays. This is the result of the parameter values, which in this case are both more negative than the travel time parameter.

8.6.3 Combined arrival time and departure time scheduling delays

When both arrival time and departure time scheduling delays are included in the departure time choice model (Equations (8.5), (8.6), and (8.7)), deviations from the preferred departure times are expected to be the smallest. This is because the parameter values of each of the scheduling components (see Table 8.8) are similar in size when compared to values in the choice models for separate departure and arrival scheduling delays. The total disutility of rescheduling a trip thus increases with equal shifts, giving these shifts lower probabilities of being chosen.

$$ASDE_{ai}^u = \max \{PAT_i^u - t_{ai}^u, 0\}, \quad ASDL_{ai}^u = \max \{t_{ai}^u - PAT_i^u, 0\}. \quad (8.5)$$

$$DSDE_{ai}^u = \max \{PDT_i^u - t_{ai}^u, 0\}, \quad DSDL_{ai}^u = \max \{t_{ai}^u - PDT_i^u, 0\}. \quad (8.6)$$

$$U_{ai}^u = \beta_{\theta}^u \theta_{ai}^u + \beta_{\tau}^u \tau_{ai}^u + \beta_{dsde}^u DSDE_{ai}^u + \beta_{dsdl}^u DSDL_{ai}^u + \beta_{adse}^u ASDE_{ai}^u + \beta_{asdl}^u ASDL_{ai}^u + \varepsilon_{ai}^u \quad (8.7)$$

Table 8.8: parameter values for combined departure and arrival time scheduling

variable	parameter	car	freight
Charge	β_{θ}^u	-0.1158	-0.0422
Travel time	β_{τ}^u	-0.0247	-0.0247
ASDE	β_{asde}^u	-0.0292	-0.0292
ASDL	β_{asdl}^u	-0.0339	-0.0339
DSDE	β_{dsde}^u	-0.0162	-0.0162
DSDL	β_{dsdl}^u	-0.0791	-0.0791

As expected, Figure 8.17 shows that, indeed, the departure time shifts are smaller than with departure or arrival time scheduling. Furthermore, as with departure time scheduling, and as a result of the high penalty for departing late, no shifts to later departure times than preferred are made in this test run. For commuter trips, as are modelled here, this is not an unlikely situation.

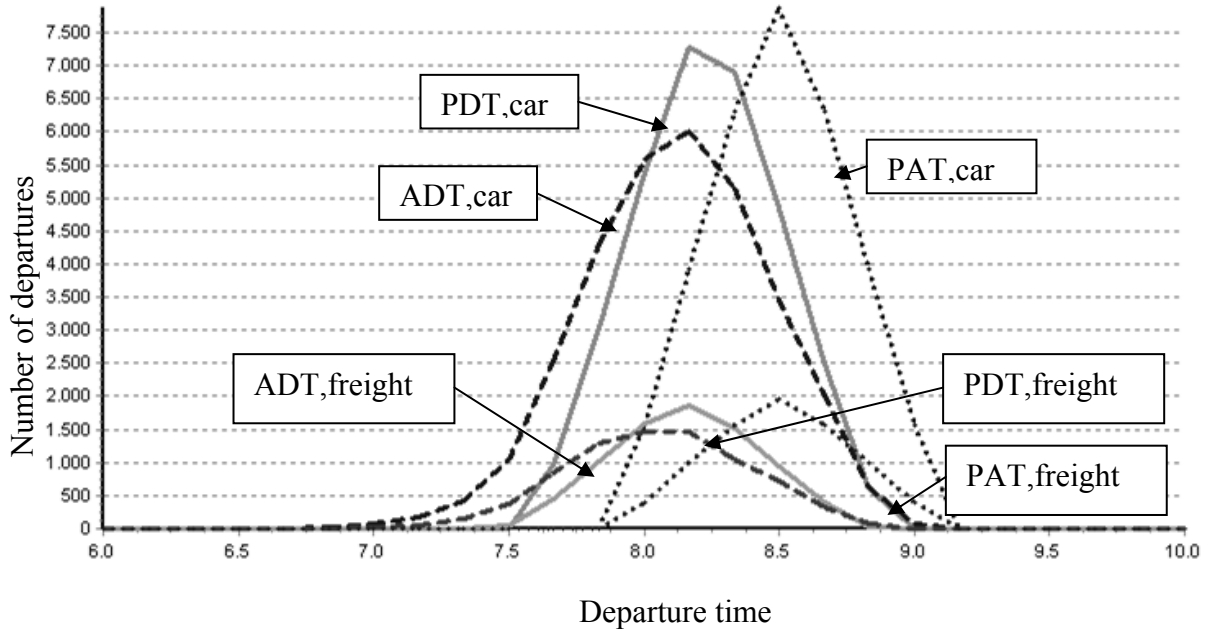


Figure 8.17: Actual departure time and preferred departure and arrival times using both departure time and arrival time scheduling delays [after 30 iterations]

8.6.4 Comparison of scheduling delay specifications

The three different specifications of scheduling delays lead to very different traffic flow patterns. The departure time scheduling delay specification is the least restrictive in departure time adjustments, which is mainly caused by the low scheduling delay early penalty. This scheduling delay specification therefore leads to the lowest total time spent on the network (see Table 8.9), as well as to the lowest mean travel time. The resulting departure time profile

does not, however, appear very realistic, due to the large amount of shifts to earlier departure times.

Table 8.9: Comparison of network indicators for different scheduling delay models

Network indicators presented for variant	arrival time scheduling	departure time scheduling	combined scheduling
Network indicators for car			
The total travel time spent on the network [hours]	9612	7857	9968
Total distance travelled on the network [km]	663660	668669	661881
Total number of vehicles put on the network	31499	31499	31499
Mean speed in the network [km/hour]	69.04	85.10	66.40
Mean travel time in the network [tt/vehicle]	18.31	14.97	18.99
Mean trip distance in the network [distance/vehicles]	21.07	21.23	21.01
Network indicators for freight			
The total travel time spent on the network [hours]	2799	2420	2840
Total distance travelled on the network [km]	165716	167074	165282
Total number of vehicles put on the network	7874	7874	7874
Mean speed in the network [km/hour]	59.19	69.03	58.19
Mean travel time in the network [tt/vehicle]	21.33	18.44	21.64
Mean trip distance in the network [distance/vehicles]	21.04	21.22	20.99

Based on the results from the test runs, the departure time choice model causes the shift in preferred departure times to occur as expected. This provides additional confidence in the model framework. Also, the specification of scheduling delays, with combined departure and arrival time scheduling delays, seems to provide sensible shifts in departure times.

8.7 Conclusions

In this chapter, test runs were conducted for the model framework using a simplified network of the city of Delft in the Netherlands. The framework was tested on route choice modelling, departure time choice modelling, the application of elastic demand, and equilibrium conditions of the framework. It was also tested for situations that included different types of toll, namely: a point toll on a single link, differentiated by user class, a time differentiated kilometre charge and a user class differentiated kilometre charge. The results of the tests show that, in all cases, the model framework performs as expected and that, more specifically:

- the route set generation is important to get route choice right;
- route choice needs, in this test model, about 5 iterations to reach a satisfactory level of equilibrium;
- departure time choice works, and different specifications of scheduling delays lead to other equilibrium traffic conditions;
- departure time choice needs, in this test model, about 8 iterations to reach a satisfactory level of equilibrium;
- elastic demand works properly

9 “Spitsmijden” case study

In this chapter, the network effects of a peak avoidance reward program are assessed using the modelling framework as discussed and tested in the previous chapters. In the peak avoidance program, called “Spitsmijden”, commuters receive a monetary incentive if they do not travel by car to work during the morning peak. The details of the “Spitsmijden” program are presented in Section 9.1.

The purpose of this chapter is twofold. Its main purpose is to demonstrate how the modelling framework was applied on a real road pricing study, albeit a negative pricing project. The second purpose is to investigate the potential network effects of the “Spitsmijden” program after large scale implementation.

As a result of applying the modelling framework on a real road pricing situation, this chapter covers issues concerning: 1) the calibration and setup of a practical and validated reference case model and 2) the analyses of changes in dynamic network condition due to different road pricing measures.

A scenario approach was adopted to determine the network effects of several “Spitsmijden” scenarios, in which the reward levels and levels of participation were systematically changed to determine the effect of each design variable and their interactions. In this approach, our modelling framework was applied to determine the network conditions in each of the “Spitsmijden” scenarios.

The main contributions of this chapter are the application of an advanced dynamic modelling framework for an actual road pricing project that considers rewards rather than tolls to persuade commuters not to travel by car in the morning peak.

The outline of this chapter is as follows. First, we discuss the setup of the “Spitsmijden” program in more detail. We then present the model setup and parameter values used in the “Spitsmijden” model. And, before discussing the model results, the setup of scenario approach is first explained. The chapter is concluded with conclusions concerning the modelling framework as well as the “Spitsmijden” reward program.

9.1 Introduction of “Spitsmijden”

Spitsmijden is Dutch for “avoiding peak hours”. During a 50 working day period, program participants were given incentives if they did not travel by car from Zoetermeer to the Hague during the morning peak (see Knockaert et al. (2007)).



Figure 9.1: Research area The Hague – Zoetermeer (Source: Google Maps)

Two types of incentives were used: 1) a monetary reward per trip avoided and 2) a smartphone could be earned based on credits per trip avoided. The purpose of the experiment was to study whether reward stimuli could be a possible control instrument to influence mobility behaviour. To this end, several surveys (including a stated preference survey) were conducted prior to and after the actual experiment. The actual experiment was launched on 2 October, 2006. The morning rush-hour was defined as lasting from 07.30 to 09.30h, since this period has the highest traffic densities. Commuters participated in the program on a voluntary basis, though some restrictions and rules were set for participation. The following were the main rules of the program:

- Participants were to commute at least three times per week from Zoetermeer towards The Hague;
- They were to have access to e-mail and the Internet;
- They were to complete questionnaires and travel logs completely and in a timely fashion;

- Their participation had to be voluntary (although they were required to sign a contract listing the rights and duties of both parties);
- They would receive a reward only for the number of times they avoided the morning rush-hour by travelling outside the rush hour period, using another mode of transport or working at home. The frequency of rush hour avoidance was determined relative to each participant's usual commuting behaviour;
- The participants who were participating in the variant had to switch on the smartphone during each car trip;
- The participants would use the car in which an On Board Unit (OBU) had been installed.

Upon registration, the participants were asked which type of reward they would prefer. Again, there were two options. The first type of reward was an amount of money for each morning rush hour that the participant avoided. At the moment of registration the premium was indicated to amount to about € 5. The second type of reward was saving for a smartphone. These participants received a smartphone at the beginning of the trial, which provided them with traffic information during the trial. If the number of avoided car trips during the morning rush hour exceeded a stated number, the participant would be allowed to keep the smartphone at the end of the trial. If the participant failed to meet the threshold, he / she would have to return the smartphone at the end of the trial.

The majority of the participants chose a monetary reward. As the trial was set up to test both reward types, the remainder of the participants (including those who had said that they did not have a preference for one reward type over the other) were assigned to the variant. However, to prevent participants ending up with an unwanted and hence undervalued reward type, they were allowed to switch to the other type prior to the start of the trial.

During the system's weeks of testing, after installing the necessary in-car monitoring equipment, data were collected about the current travel behaviour. The measurements on current behaviour served as a reference for both the analyses on changes in behavioural analysis as for determining if participants were eligible for a reward on a specific day. The former motivation is the main reason that the participants had to complete their logbook during the test weeks, and the latter argument is why we did not tell the participants what we were actually measuring, in order to avoid any bias in reference (unrewarded) behaviour.

9.1.1 Monetary reward option

During the ten-week reward period, the participants could obtain a reward by avoiding the rush-hour. In order to maximize the behavioural information, three reward levels were tested for:

- € 3 reward for avoiding the 07.30 – 09.30h period for three weeks;
- € 7 reward for avoiding the 07.30 – 09.30h period for four weeks;
- € 3 reward for avoiding the 08.00 – 09.00h period, increased to € 7 if the full rush hour (07.30 – 09.30h) was avoided, for three weeks.

Although all the participants dealt with all three reward levels for the same number of weeks, the order of the three variants was shifted in order to compensate in the analysis for any order-related bias.

9.1.2 Smartphone reward option

The participants of the smartphone option underwent a similar scheme of two reward-free weeks plus one reward-free week at the beginning and at the end of the trial, respectively. For

the participants, the aim was not only to measure the impact of a reward but also to test for the impact of traffic information. It was therefore decided to increase the number of reward-free weeks. This led to two reward levels (the participants were assigned evenly to both schemes) during the ten-week period, namely:

- avoiding enough rush-hours in order to be allowed to retain the smartphone and subscription to the traffic information service;
- For another period of five weeks: only receiving traffic information.

9.2 Model setup: network, travel demand, and traffic data

This section gives the model setup for evaluating the effects of “Spitsmijden” scenarios. The purpose is to clearly describe how the general modelling framework presented in previous chapters was applied on the “Spitsmijden” case study. The section deals with the following issues: 1) network infrastructure, 2) travel demand, 3) choice model parameters, 4) available traffic count data, and 5) model calibration results.

9.2.1 Network infrastructure description

The research area – the area of main interest – consists of the area around The Hague and Zoetermeer, and is bounded from the north by Leiden, bounded from the south by Rotterdam, bounded from the east by Gouda, and bounded from the west by the North Sea (see Figure 9.1). The road network considered in the traffic model is depicted in Figure 9.2.



Figure 9.2: Transportation network in traffic model

In total there are 1891 links and 1133 nodes in the network. For each link, the following attributes are known:

- length of the road segment [km];
- speed limit [km/h];
- number of lanes;
- capacity [veh/h];
- speed at capacity [km/h]

The model that will be used is mainly for motorway traffic and does not take delays at intersections into account; hence the data on (signalized) intersections will not be used.

9.2.2 Travel demand description

In this research, the focus is on the morning peak (from 6:00am to 11:00am), in which the main travel demand is for commuting trips from home to work. In total, there are 168 zones in the model (see Figure 9.3). The total number of trips in the static OD matrix is 473,868, of which 40,722 originate from Zoetermeer and 8,475 have a destination in The Hague. The latter also being the maximum number of participants for the Spitsmijden program in the model.

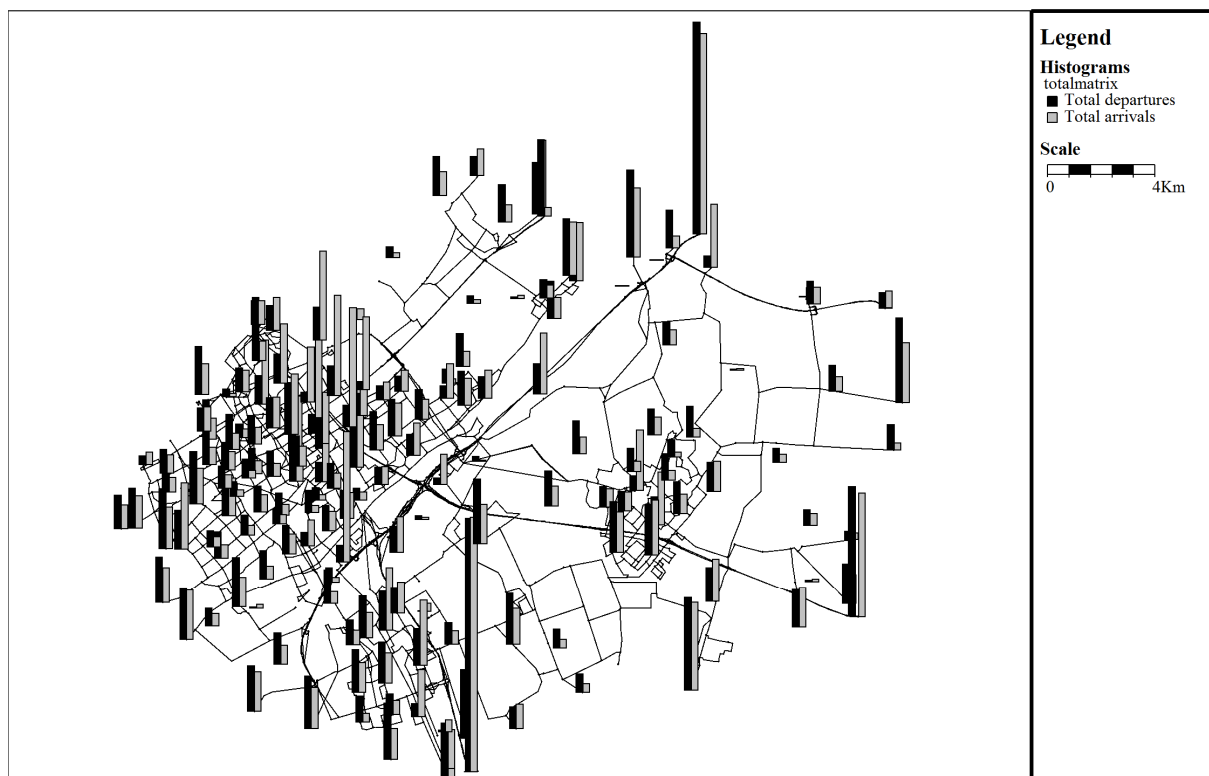


Figure 9.3: Total number of departures and arrival per zone

9.2.3 Travel behaviour choice model parameters

The main parameters to be set in the travel behaviour models are in the generalized cost functions, the scale parameters in the multinomial logit models, the trip elasticity for car travel demand, and the distributions of the preferred arrival times.

The parameters of the departure choice models, see Table 9.1, stem from two separate stated choice experiments. For non-participants, the departure time choice model based on the stated choice experiment in Part B of this dissertation is used. For participants, the stated choice

experiment and resulting departure time choice model from the pilot project was used as described in Knockaert et al. (2007). The scale parameters for both departure time choice models were calibrated and set at a value of 4.

Table 9.1: Parameters used in the generalized cost function

Parameter	Non-participants	Participants
β_t^u (time) [min]	-0.0247	-0.0220
β_c^u (reward) [euro]		0.2490
β_{dsde}^u (early departure) [min]	-0.0791	-0.0147
β_{dsdl}^u (late departure) [min]	-0.0162	-0.0137
β_{asde}^u (early arrival) [min]	-0.0292	
β_{asdl}^u (late arrival) [min]	-0.0339	

The initial distribution of preferred arrival times (PAT) for non-participants is calibrated such that the model fits the traffic data as described in subsection 10.2.5. The distribution of preferred arrival times (PAT) for participants is derived from the pilot survey. In a second step, the PAT profile of non-participants is adjusted for each level of participation in such a way that the total PAT profile (participant and non-participant combined) is equal to the initially calibrated non-participant profile. The resulting preferred arrival time profiles are shown in Figure 9.4.

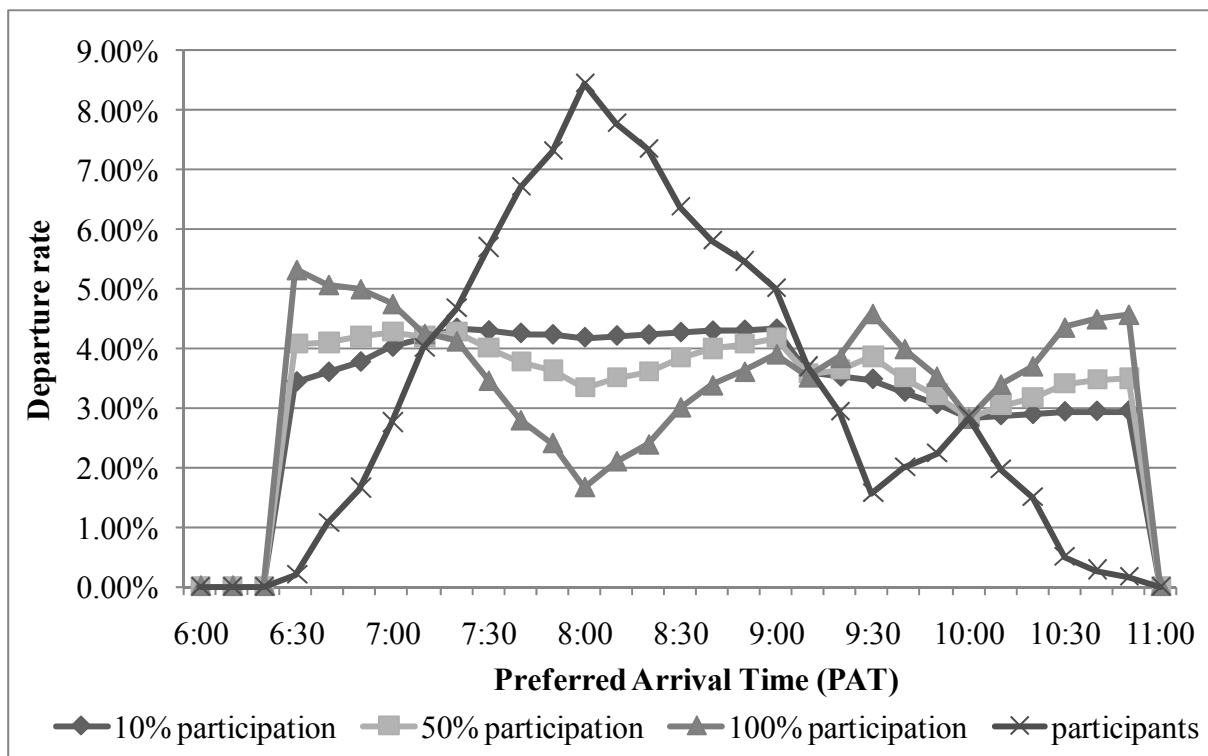


Figure 9.4: Preferred arrival time (PAT) distributions

Of the participants, most travellers prefer to arrive at around 8:30am. Note that there is a small group of travellers that prefers to arrive after the morning peak, at around 10:00am - 10:30am.

The preferred departure time profiles are computed from the preferred arrival time profiles using the free-flow travel time between each OD-pair. Thus, depending on the free-flow travel time, the preferred departure time patterns can be quite different for individual OD-pairs.

Finally, the trip elasticity for car travel demand turned out to be very small in the actual experiment, which means that travellers are not likely to change to other modes of transportation, work from home, etc. In the long run, it is, however, unlikely to assume a trip elasticity of zero. Also, the number of trips of non-participants may change as a result of changing traffic conditions. In the model, the elasticity of non-participants was set to -0.2 and for participants to -0.25 .

9.2.4 Traffic data

The trips between the zones on the transportation network yield network traffic as can be observed on the roads and measured using loop detectors (see Figure 9.5). These loop detectors are present on the motorways and on some other major roads. For this research, we had access to traffic data on a number of locations on the A4, A12, and A13 motorways, see Figure 9.6, including amongst others (for each 1 minute time period):

- the flow (veh/h)
- the average speed (m/s)

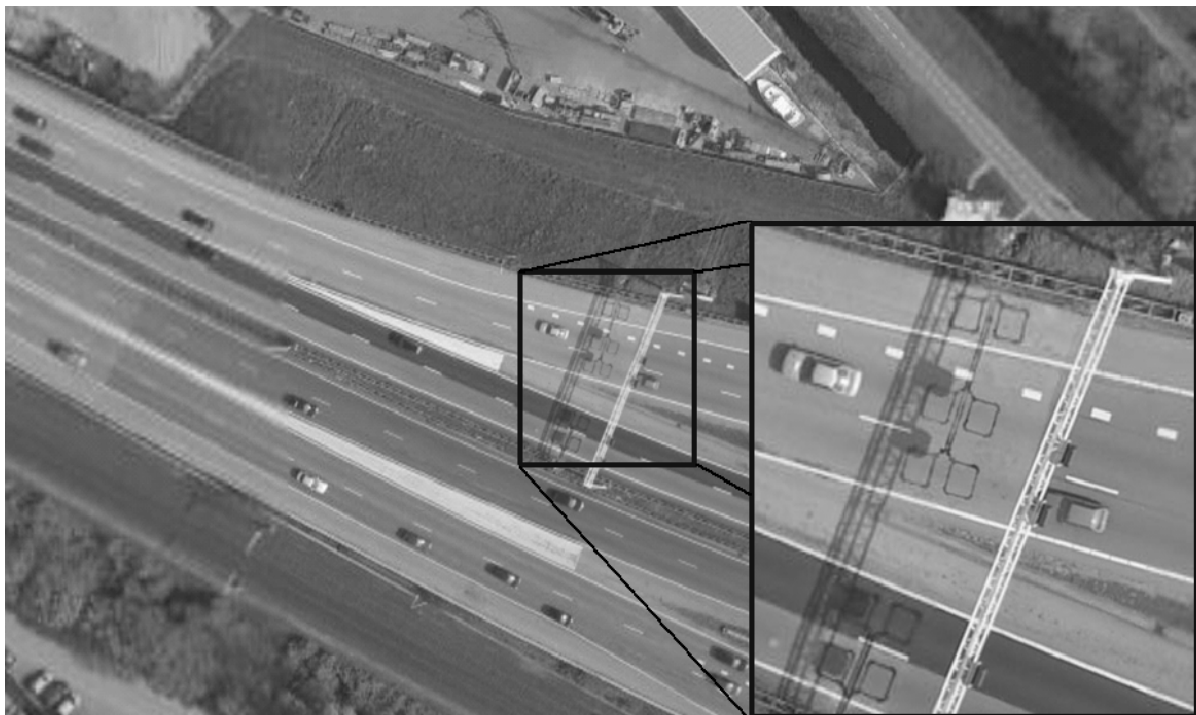


Figure 9.5: Loop detectors in the road (source: Google Earth)

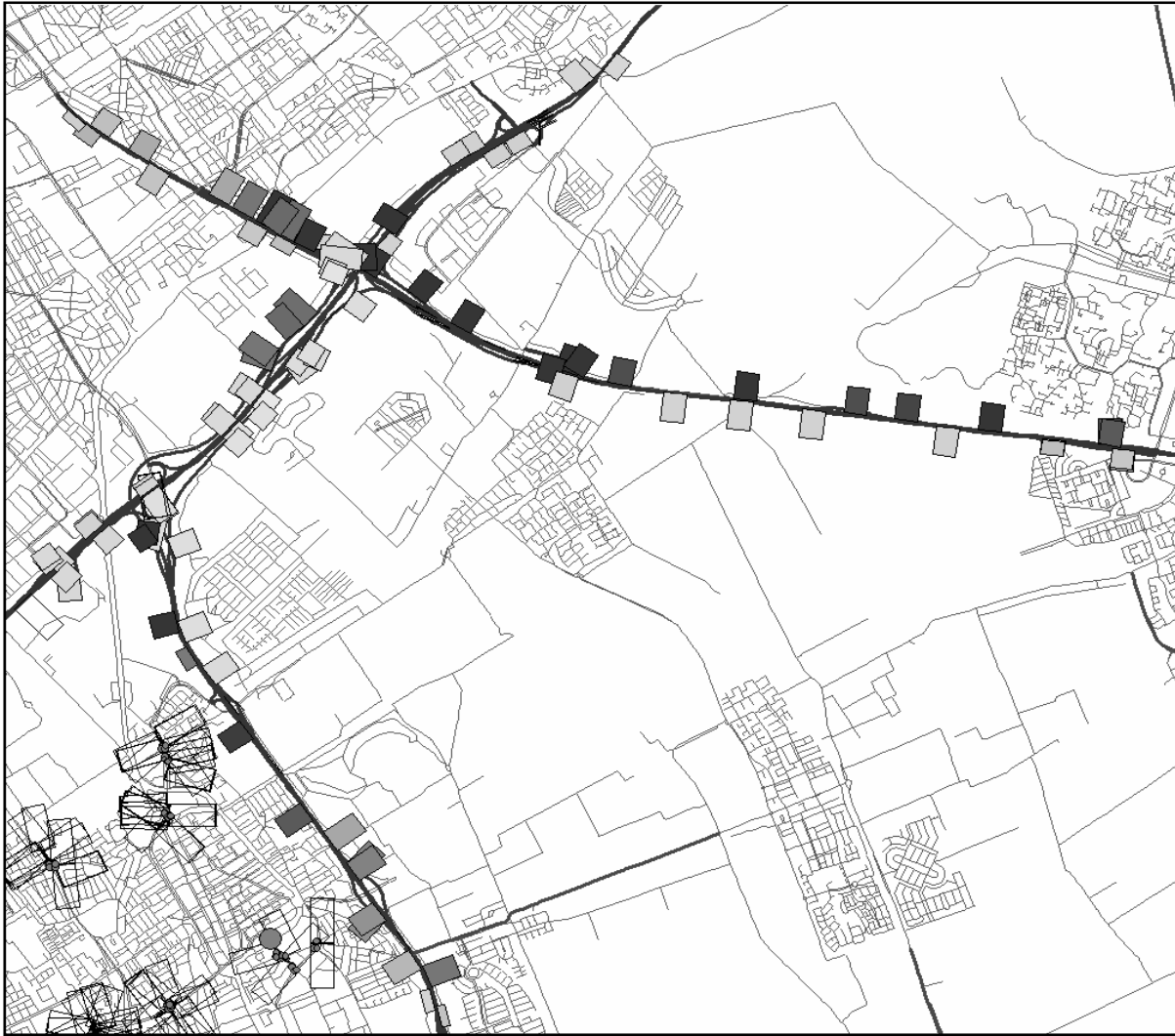


Figure 9.6: Location of loop detectors

Figure 9.7 shows the trajectory plot from Gouda to The Hague along the A12 motorway, while the bottom figure indicates the travel times from Gouda to The Hague, all over a period of 24 hours. In this case, it displays the data for Tuesday, April 4th, 2006. The 2006 data has been analyzed and visually inspected in order to find an ‘average daily traffic pattern’. The traffic patterns vary from day to day. There are, however, common patterns to be observed. The selected day, April 4th, 2006, seems to present a typical daily pattern in terms of flows and travel times. Clearly, from the travel time plot in the lower figure, it can be observed that during the morning peak, there is significant congestion on the A12 towards The Hague, where the free-flow travel time of approximately 17 minutes increases to a travel time of somewhat less than one hour travel time at around 8am.

In the trajectory plot, the congested locations and times are indicated with low speeds. From this figure, it can be easily seen that in the morning peak queues build up on the A12 at 3 specific locations:

- (a) at on-ramps from Zoetermeer;
- (b) at (or just after) Prins Clausplein;
- (c) at the traffic lights at end of the Utrechtsebaan.

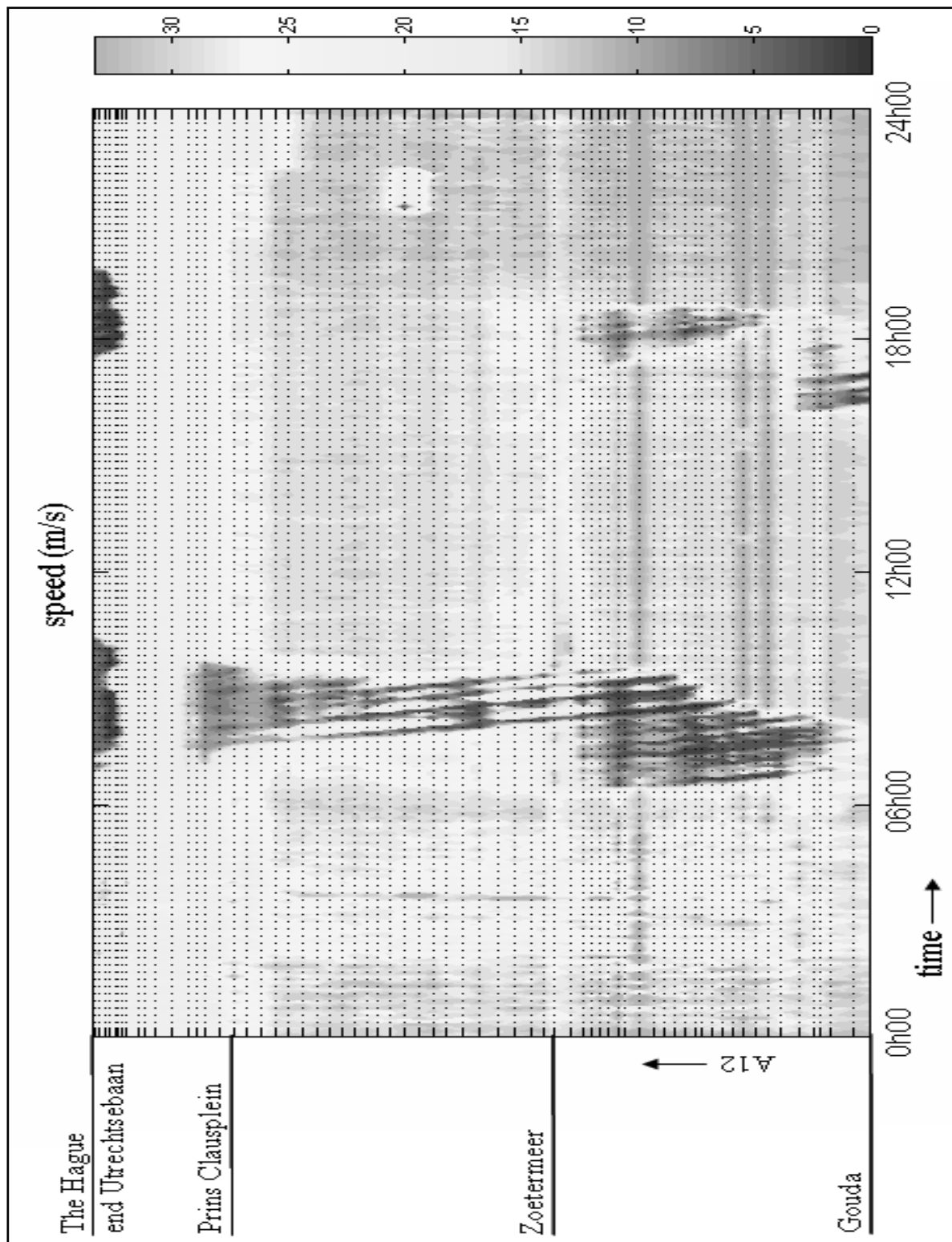


Figure 9.7: Motorway A12 trajectory plot (April 4th, 2006)

9.2.5 Model calibration results

The traffic simulation model has many parameters that can be calibrated. Besides the parameters for the link characteristics (such as capacity), some general parameters need to be set as well (such as the minimum speed and the jam density per lane). Furthermore, the cells in the travel demand OD matrix that are used as input may have to be altered. In order to calibrate these parameters and OD matrix cells, the outcomes of the traffic simulation (for the

reference scenario in which no SpitsMijden rewarding scheme exists, i.e. the ‘current situation’) are compared to the traffic data collected.

The calibration process was carried out in two stages. In the first stage, we concentrated on calibrating the link flows in the network, such that the numbers of cars on the roads are accurately replicated in the model. This is done using a maximum likelihood estimation procedure which changes cells in the initial OD matrix (Omnitrans International (2009)). In the second stage, the static OD matrix is split into 10 minute demand periods by changing the preferred arrival time profile for non-participants and comparing the model results with travel time, densities and flow measurements. This whole calibration process is a time consuming and computationally intensive exercise. In the end, a traffic pattern emerged from the model that was a sufficiently accurate representation of the ‘current situation’, suitable for analyzing case studies. Comparisons between the modelled and measured traffic flows, as well as the modelled and measured traffic densities, are given in Figure 9.8 and Figure 9.9, respectively. Both match quite well. For the results shown here, the spillback option in the traffic simulator in INDY was disabled in order to speed up computation times. Ignoring spillback of congestion complicates the calibration process, because the total delay of a bottleneck needs to be modelled in a single link. Ideally, the model would be run using spillback in order to improve the travel time forecast. Figure 9.10 shows the resulting comparison of modelled and measured travel times in the A12 corridor between Zoetermeer and The Hague.

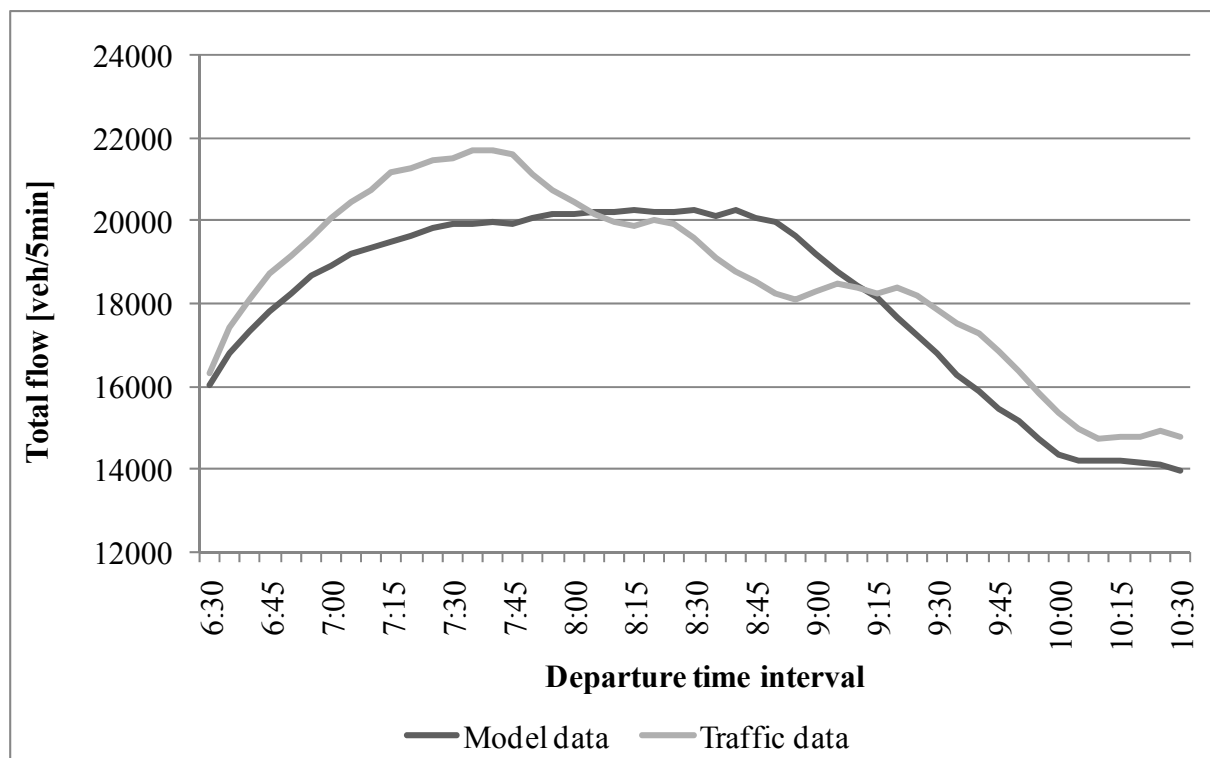


Figure 9.8: Modelled and measured traffic flow over time

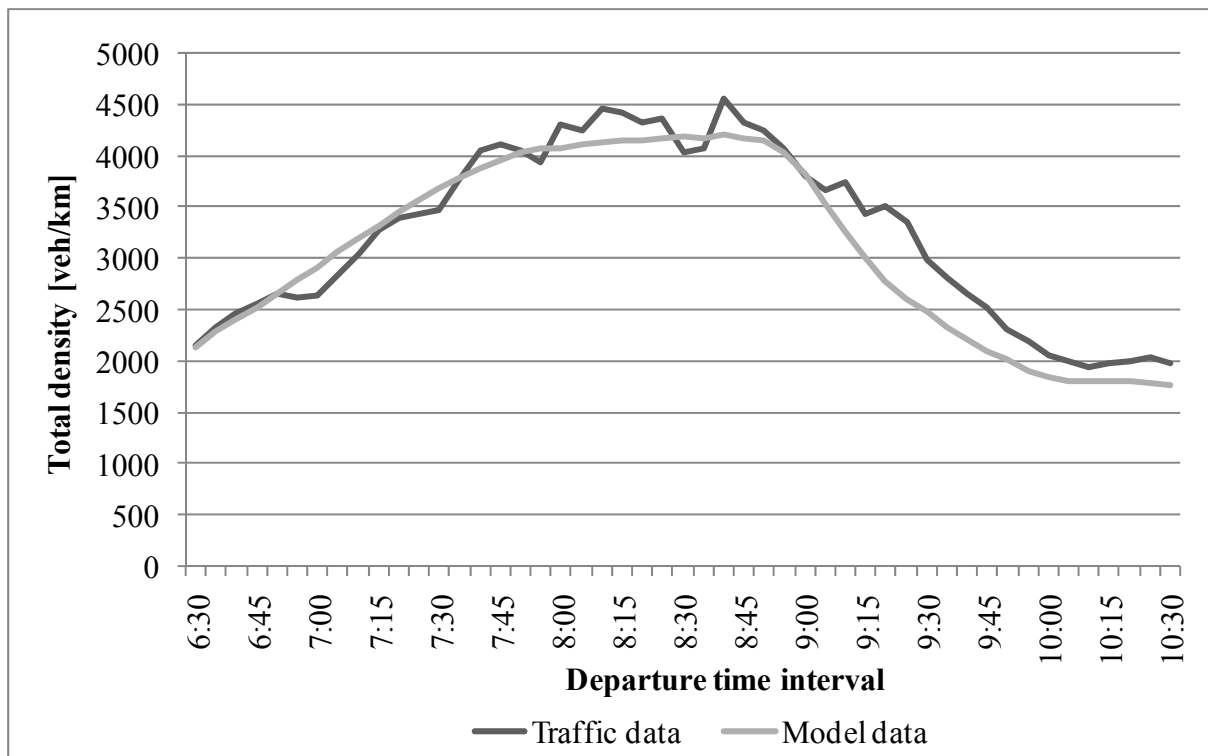


Figure 9.9: Modelled and measured traffic densities [veh/km] (summed over all measurement points) over time

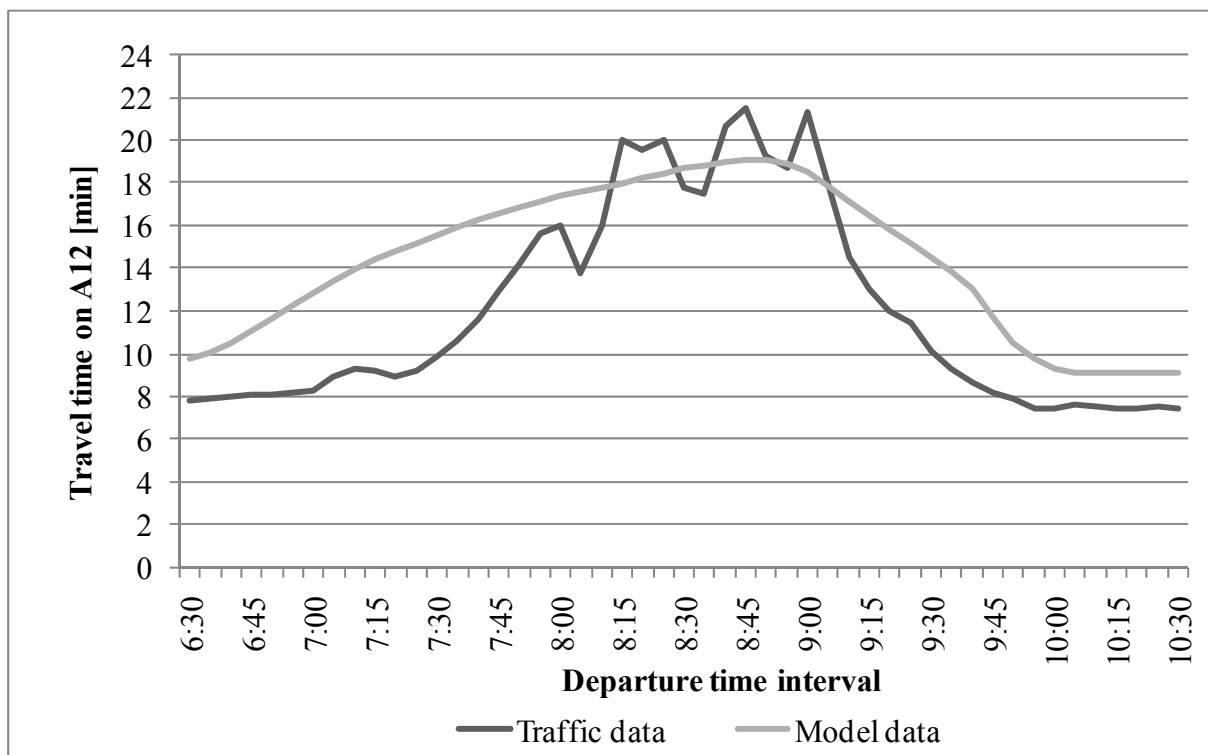


Figure 9.10: Modelled and measured travel time from Zoetermeer to The Hague

9.3 “Spitsmijden” strategies

In order to investigate the effect of the participation level and the level of the reward on travel behaviour and traffic conditions, different scenarios are examined. In these, we change the participation level of travellers from Zoetermeer to The Hague to levels of 10%, 50%, and 100%, respectively. The reference cases also use these participation levels while no reward for avoiding the peak period is used. Note that participation is limited to travellers from Zoetermeer to The Hague only, as the “Spitsmijden” reward scheme is tailor-made for these travellers by providing a reward on the A12 motorway.

The rewards levels we distinguish are: €1, €3, €5, and €7; except for the 1 euro, this is consistent with the rewards that are used in the pilot study. These are rewards to be earned if travellers are not detected travelling from Zoetermeer to The Hague between 7:30am and 9:30am. For the model studies, the rewards are assumed to be fixed and do not vary over time, although the model does allow time-varying rewards. This will be examined in further research.

Table 9.2 summarizes the different scenarios with varying participation levels and reward levels. Scenarios 1, 2b, and 3 will be analyzed to draw conclusions on the effect of the participation level on travel behaviour and traffic conditions. Scenarios 2a, 2b, 2c and 2d will be analyzed in order to draw conclusions regarding the effect of the reward level. Scenarios 0a, b and c are the reference scenarios, which serve as the basis for comparison. The model results and these analyses are presented in the next subsection.

Table 9.2: Scenario’s with different levels of participation and rewards

Scenario	Participant level	Reward
0a (reference)	10%	€ 0
0b (reference)	50%	€ 0
0c (reference)	100%	€ 0
1	10%	€ 5
2a	50%	€ 1
2b	50%	€ 3
2c	50%	€ 5
2d	50%	€ 7
3	100%	€ 5

9.4 Model results

The Scenario results will be presented in the following subsections. First of all, in Section 9.4.1, the effect of the participation level will be analyzed. Then, in Section 9.4.2, the effect of different reward levels are examined. In Section 9.4.3, the model outcomes are discussed.

9.4.1 Effect of changing levels of participation

Figure 9.11 presents the results of different participation levels on the total network travel time for both participants and non-participants. A participation level of 50% generates travel time losses, while both a participation of 10% and 100% lead to travel time savings. Scenario 1 (10%) causes a small amount of traffic to shift departure times, which leads to travel time savings for participants because they travel during less busy periods. The reduction of traffic during the peak (between 7:30am and 9:30am) also causes travel time savings for the non-participants. In Scenario 3 (100%), a large group of participants changes departure time, see

Figure 9.12. This again leads to travel time savings for participants, although less per participant because the shifts of large groups causes congestion before and after the peak. Demand inside the peak is much lower, which results in improved travel conditions. Scenario 2b (50%) causes the worst of both worlds. The group that shifts is large enough to cause some delay for the participants themselves, but the traffic condition at the start of the peak, combined with a still high level of demand, mainly causes traffic conditions to worsen for the travellers inside the peak.

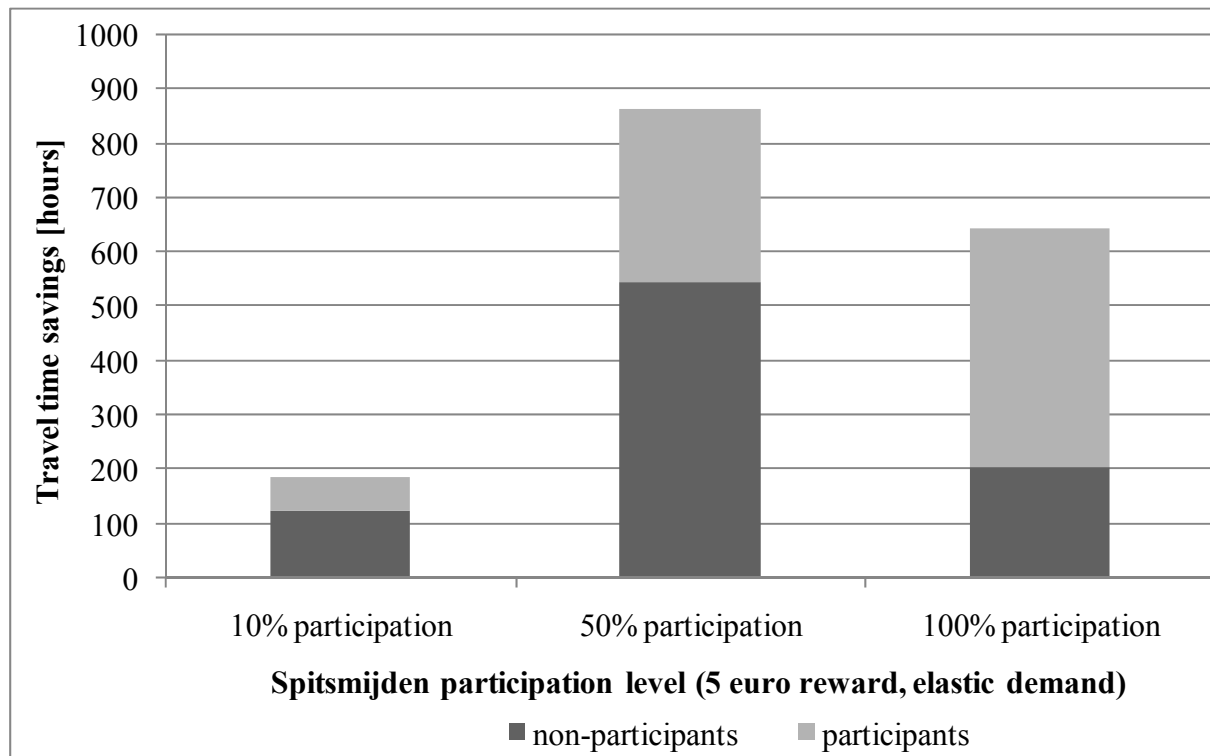


Figure 9.11: Effect of participation level on total network travel time savings

Figure 9.13 depicts the percentages of participants that receive a reward. This clearly shows a decreasing percentage of participants receiving a reward. However, the total number of participants increases more heavily than the percentage in reward decreases.

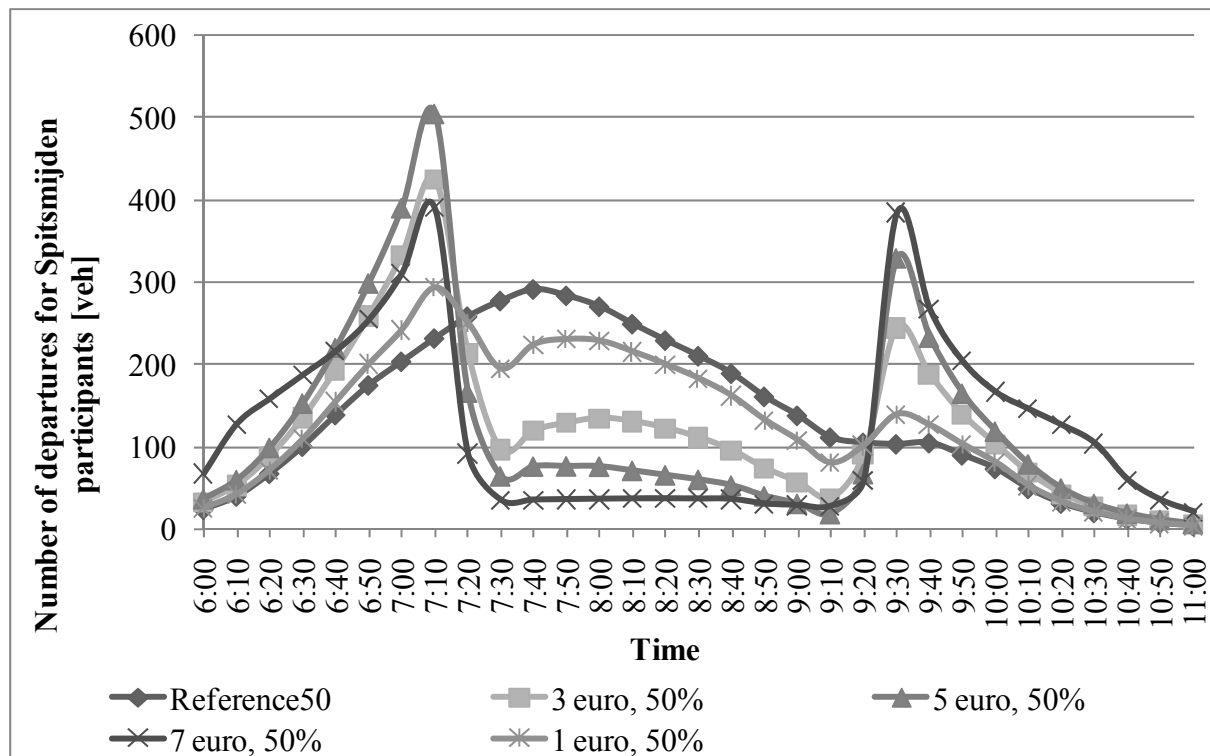


Figure 9.12: Departure time adjustments of participants

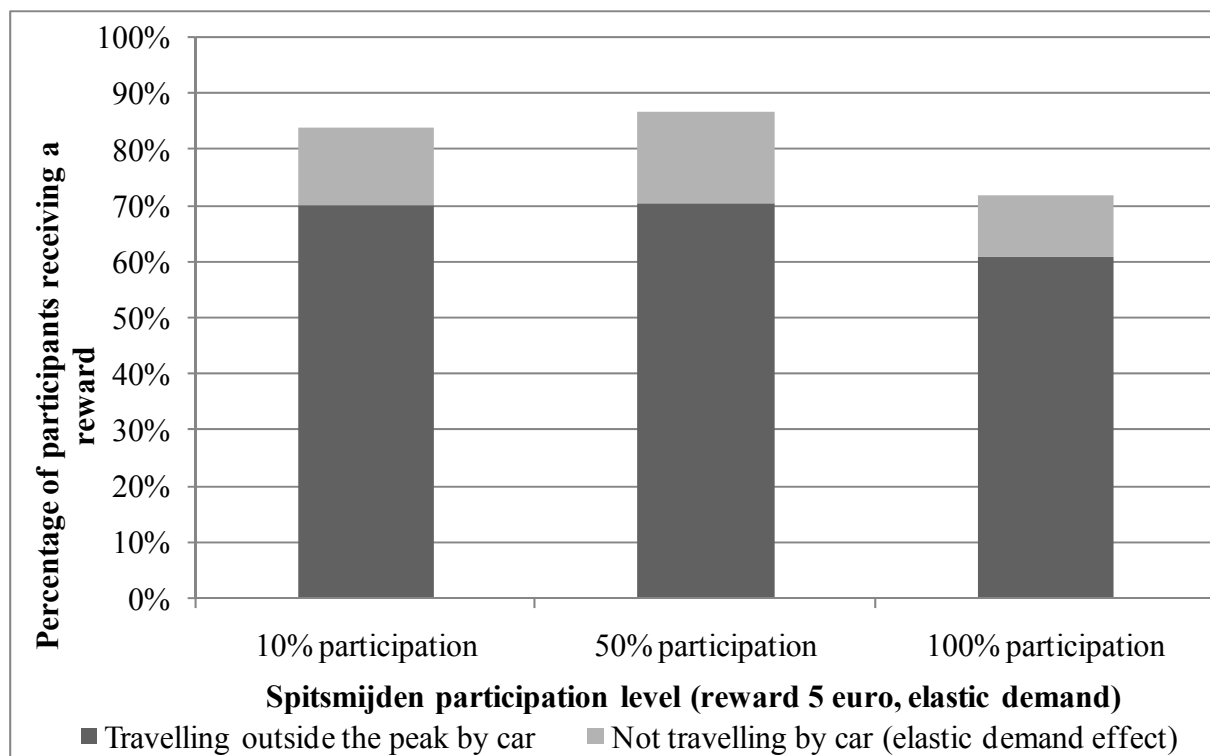


Figure 9.13: Effect of participation level on number of rewards received

9.4.2 Effect of changing reward levels

Changing the level of rewards causes a similar effect on total travel time saved as changing participation level (see Figure 9.14). A small number of participants that changes departure time can alleviate the congestion for many: the 3 euro case, 2a. If too many people change, they cause congestion for themselves and others: the 5 euro case, 2b. Finally, some travel time

saving can be achieved at even higher levels of participation. In case 2c, the participants do achieve some travel time savings for themselves, but leave much congestion behind for the non-participants that travel later.

Higher reward levels are expected to trigger larger behavioural effects. This shows in Figure 9.15. As the reward levels increase, the percentage of participants that changes their behaviour to travel outside the peak also increases. Note that this percentage does not include participants that already travel outside the peak and who also receive a reward even without changing their behaviour. The increase in change in behaviour to travelling outside the peak is larger between case 2a and 2b than it is between case 2b and 2c.

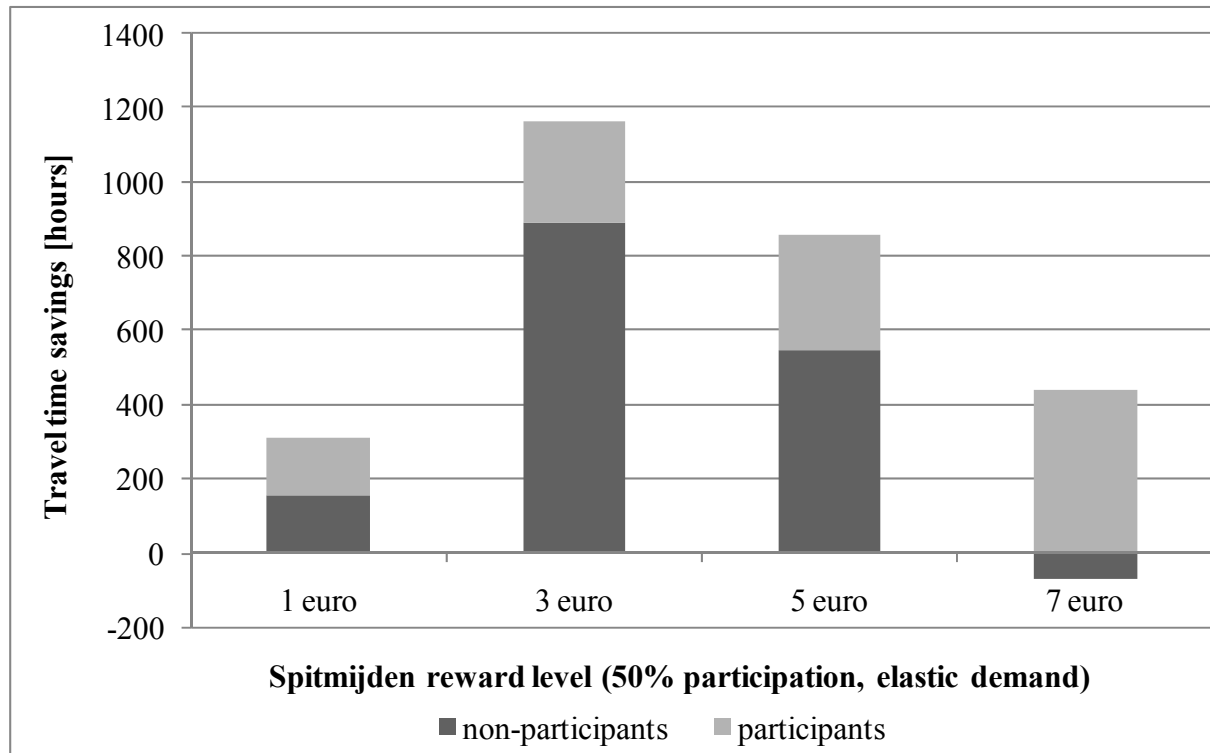


Figure 9.14: Effect of reward level on total network travel time savings

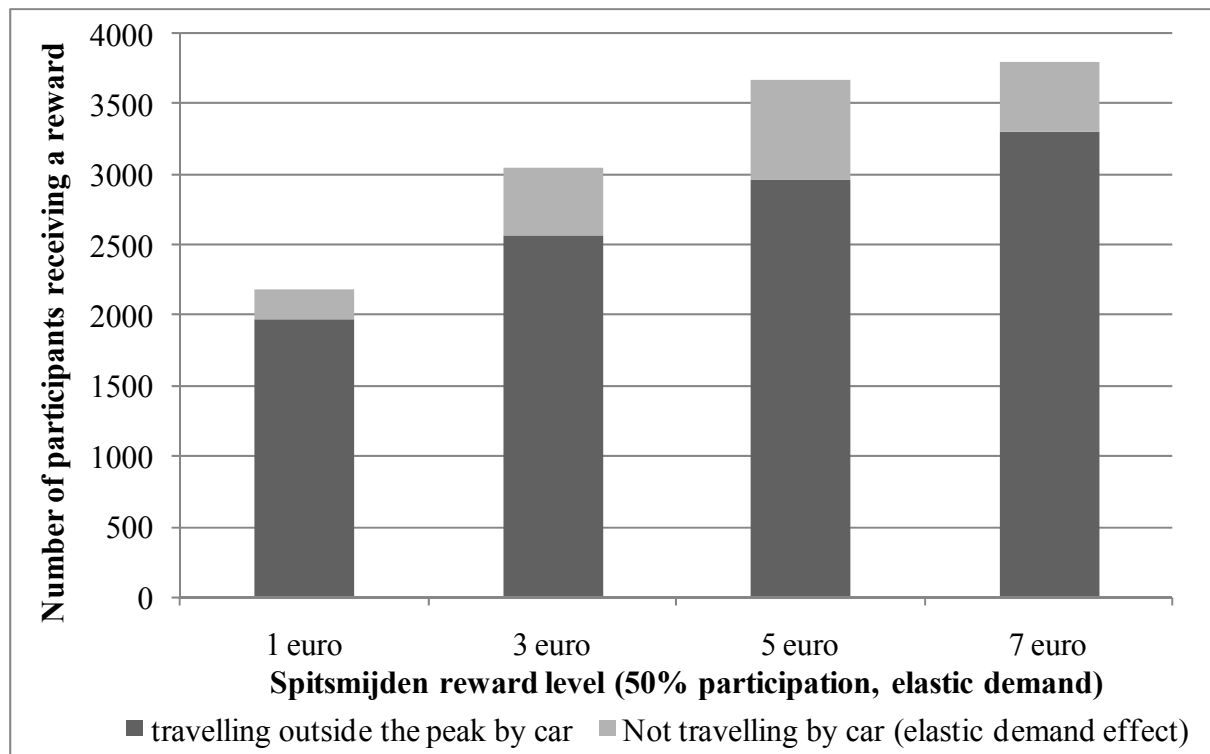


Figure 9.15: Effect of reward level on number of rewards received

9.5 Conclusions

From the model results, there seems to be a trade-off between the number of participants that can earn a SpitsMijden reward and the level of the reward. A high level of participation with high rewards, which in reality would correlate if participation were voluntary, will probably lead to delays before the peak. These delays and queues will negatively impact other travellers as well, resulting in net travel time losses for the whole network. In practice, this combination of high reward and participation would also be very expensive. The largest travel time savings can be achieved by shifting a low enough number of travellers that they do not cause congestion for themselves and others, while decreasing demand during the peak to below capacity, thus solving the bottleneck. In the cases examined here, the 3 euro and 50% participation (case 2a) or the 5 euro and 100% participation (case 3) cause the largest travel time saving. There may exist an optimal combination that would yield the best traffic conditions for all car drivers, but we cannot conclude this from the few case studies presented in this report.

These case studies present some preliminary results from a network modelling exercise. Including the trip choice elasticity in the model, running the model in a spill back mode and running more case studies would be the next step in order to investigate the impact of a SpitsMijden rewarding scheme on travel behaviour and traffic conditions. The fixed time interval for receiving rewards which is currently used in the different cases is also a topic of research. Of interest is, further, what such a SpitsMijden rewarding scheme would look like if it was open for participation for all travellers in the whole area, or even the whole country, and what impact this would have on the traffic conditions. The impacts simulated in this study are local impacts on a small part of the transportation network, and are therefore only affecting a proportion of all travellers. A broader implementation would yield effects on a much larger scale.

PART D: Synthesis

Conclusions

In this thesis, we investigate the behavioural responses and network effects of time-varying road pricing and we start with looking at the objectives and design dimensions of road pricing measures. We conclude that the objective, although not uniquely, determines the design of a road pricing measure. This conclusion may be a simple one, but in the political arena, the objectives of road pricing are often unclear or multiple objectives are defined that may contradict. It seems that, at least in the Netherlands, the political discussion on road pricing starts with discussing different measures instead of with discussing the objectives and intended effects.

In designing road pricing measures, we distinguish primary and secondary design dimensions. The primary design dimensions together determine how much a traveller has to pay for a specific trip, while the secondary design dimensions determine how the traveller is informed about this and how he may use the system to pay. Our research into the behavioural responses of commuters towards road pricing showed that in some of the choice models, the attribute of road pricing was also significant. This finding, to some extent, supports our conclusion that there is more to road pricing than just the price people pay. The price is not the only stimulus.

In order to investigate this issue further, we developed a stimulus-response framework that identifies the relationships between a road pricing measure (the stimuli), the choice behaviour of decision-makers (the response), and the traffic system effects. The complexity of behavioural responses and the interactions with subsequent system changes clearly show that road pricing is a multi-disciplinary topic of practise as well as research. We conclude that in designing road pricing measures, a good starting point will be to describe the desired behavioural changes of travellers and from this deduct how the primary design dimensions should be set and how secondary design dimension can further support the effectiveness of the measure.

Based on the theoretical stimulus-response framework, a unique dedicated empirical data set has been established using a stated choice experiment with the purpose of gaining insights into commuters' responses, testing of pertinent hypotheses and estimating behavioural parameters. The stated choice experiment includes commuters' route, departure time, and

mode shifts in response to time and place differentiation of road pricing stimuli. Additionally, the data include travel time unreliability as a traveller's choice attribute with a new way of operationalisation, in order to better represent the unreliability experienced in real life.

From a methodological perspective, we respect the repetitive nature of the commute trip in the stated preference experiments by having respondents distribute a given number (10) of trips among alternatives rather than by making a single choice. This innovative approach demonstrated that respondents appear more sensitive to road pricing and are more likely to change departure times than shown in traditional stated choice approaches.

Looking at the behavioural responses of commuters with respect to road pricing, we conclude that commuters have different sensitivities towards different types of costs. The road pricing charges are felt most, followed by the fuel costs and then by public transport costs. Depending on the secondary design dimensions of a road pricing measure, we expect that, in the long term, the sensitivities for fuel costs and road pricing charges might grow closer together. We also found a large difference in sensitivities between those travellers who are compensated by their employer for travel costs and those who are not. We expect that respondents who are currently receiving compensation for travel costs may expect to be compensated for road pricing fees as well. We conclude that additional policies that reduce the compensation of road pricing fees by employers will increase the effectiveness of the road pricing measures. We also find that commuters have non-linear sensitivities towards fuel costs and road pricing fees. We conclude that there exists a decreasing sensitivity towards costs as costs increase. We also conclude that the disutility of travel costs only contributes a relatively small share of the total disutility. This does not mean that in a specific choice situation, the road pricing fee cannot be the determining factor. In fact, when applying our road pricing impact model to assess the network effects, we see significant changes in behaviour and traffic conditions.

As a result of time-varying road pricing measures, we expect travellers to try to avoid time periods that are most expensive by adjusting their departure time. There is some evidence of this from implemented measures. We therefore researched, in more detail, the sensitivities of commuters to rescheduling their trip from their preferred departure and arrival times. We found that both departure time rescheduling and arrival time rescheduling are important in departure time choice, and that commuters have non-linear sensitivities towards these components. Later departure times incur higher disutilities than earlier departure times. This is to be expected for commute trips where most travellers will have to start working at a certain time. The distinction between departure and arrival time scheduling delays has previously never been made, but by making this distinction, it becomes apparent that the penalties for scheduling early are more dominated by the arrival side of the trip, while for scheduling late, the departure side of trips seems more important. In other words, commuters do not mind departing earlier as much as they do arriving earlier, while at the same time, they are more sensitive to departing late than to arriving late. In our analyses of the data we collected on the choice behaviour of commuters, we found that about 73% of the commuters in our sample can depart from home when they want, but about 55% of respondents state that they have to arrive at work within certain time limits. Arriving later than a specific time is the most reported constraint. We found that rescheduling outside the bandwidths of acceptable departure and arrival times incurs additional disutility upon commuters. Given these findings and the contribution of the scheduling disutility to the total disutility, we conclude that rescheduling of commute trips, especially to later time periods, does not seem very easy. With regards to time-varying road pricing, this implies that the effectiveness of the measure would

increase when additional measures are taken that reduce the sensitivities of commuters towards rescheduling.

We investigated the sensitivity of commuters towards travel time and different travel time components, as we expect the introduction of road pricing to impact these as well. We identified three possible travel time components for a specific trip, namely free-flow travel conditions, congested travel conditions and unreliable travel conditions. The latter being the difference between the travel time they expect to encounter and the travel time commuters need to take into account to insure a high enough probability of on-time arrival (we defined this as the anticipated travel time). There exist different approaches to determining the sensitivity of travellers towards travel time unreliability, namely the mean-variance and scheduling approach. We used a scheduling approach but conclude that either incorporating unreliability in an expected travel time or as a separate travel time attribute provides the best results in our case, both from a behavioural viewpoint and in terms of model fit. This measure of unreliability is thus not included in expected scheduling delay attributes. Furthermore, we found that travellers are most sensitive towards congested travel conditions, then towards free-flow travel conditions and lastly towards travel time unreliability. The difference in sensitivity towards congested and free-flow travel time increases with higher travel times. The sensitivities towards congested and free-flow travel conditions are non-linear, while we could not establish this for travel time unreliability. The sensitivity to travel time unreliability that we measured in this research relates to the unreliable travel conditions commuters are faced with in congested networks. The sensitivity towards unreliability as result of incidents may be different and is likely higher. We conclude that reducing congested travel conditions will benefit travellers more than reductions in travel time reliability as a result of congestion. In some cases, relieving congestion may lead to increased travel time unreliability as travel times become more variable and harder to predict.

In developing a modelling framework capable of assessing the network effects of time-varying road pricing measures, we conclude that it is essential to take time explicitly into account, as travellers may choose different times of departure, or different routes at different times, but they will for certain experience different travel conditions at different times. We developed such a dynamic modelling framework that is practically applicable and capable of assessing the network effects of time-varying road pricing measures, as it includes route choice, departure time choice and elastic demand. The modelling framework was successfully applied in different research projects to assess the network effects of different pricing related measures such as the Spitsmijden reward pilot and a pilot on Pay as you Drive car insurance.

For the assessment of potential network effects of alternative “Spitsmijden” reward scenarios, we expect that there exists an optimal combination of level of participation and of reward, as high levels of participation with high rewards lead to delays before the peak. These delays and queues negatively impact other travellers and results in net travel time losses for the whole network. In practice, this combination of high reward and participation would also be very expensive. The largest travel time savings can be achieved by shifting a low enough number of travellers that they do not cause congestion for themselves and others, while decreasing demand during the peak to below capacity, thus solving the bottleneck.

A final conclusion based on all the findings from this research and from literature we have reviewed in the course of our research is that road pricing measures do lead to behavioural responses and changes in traffic conditions, and that these behavioural responses and changes in traffic conditions can be assessed with a reasonable amount of reliability using analytical

models. In simpler words, road pricing works and it can be designed to work in a way that meets policy objectives. For some, this may be a trivial conclusion, but there are many who still believe that the only change road pricing offers is that of having to pay to drive through the same congestion.

Recommendations

Policy recommendations

Currently, there exist more plans for introducing road pricing measures than actual implementations of road pricing measures. This is not necessarily a problem, but designing and implementing road pricing measures is complex, even without considering the political process that it also entails. In this section, we will provide some policy recommendations that result from this research, which will hopefully assist different people involved in developing road pricing measures.

The first recommendation results from the conclusion that road pricing objectives and the desired behavioural responses determine the levels of differentiation in the primary design dimensions, and also the design choices for secondary design dimensions. We recommend that the designing of road pricing measures starts with a clear definition of objectives and a description of desired behavioural responses. This will result in a road pricing measure that works in the manner that was intended and can thus be explained to the public.

We found that commuters exhibit different sensitivities towards different cost components and we have even found significant charging attributes. From these findings, together with our analyses in developing the stimulus-response framework, we conclude that road pricing is comprised of more stimuli than just the price travellers have to pay for a trip. Our recommendation is, therefore, to not only consider the charge level, the differentiation in charges and the ultimate price travellers pay, but also the design of secondary design dimensions and how travellers interpret these stimuli.

From analyses we conducted on the respondents in the survey, it appeared that there exists a large group of commuters in our sample that receives compensation for their commute costs from their employer. In modelling the behavioural responses towards road pricing, we found that commuters who do receive such compensation are less sensitive to road pricing charges. Even though our sample is not representative for the Dutch population, we recommend that the existing compensation mechanisms for commute trips be taken into account when designing road pricing measures and, if it is necessary to increase the effectiveness of road

pricing, we also recommend introducing additional measures that reduce compensation of travel costs by employers.

As a result of our interest in time-varying road pricing measures and our expectation that as a result of such a measure travellers adjust their departure time, we looked in more detail at the departure time choice of commuters. We found that commuters are quite sensitive to rescheduling their commute trip, especially to later departure times. If changes in departure times are desired behavioural responses of the road pricing measure, we recommend introducing measures that reduce the sensitivities of commuters to rescheduling. These can, for example, be more flexible working hours, extended opening hours of day care centres and store or teleworking policies that allow employees to start working at home and arrive at the office later. In even more general terms, we recommend the improvement of the choice alternatives of travellers for those dimensions of behavioural responses that the road pricing measure is intended to invoke. For example, if the intention is to cause a modal shift from car to public transport, good public transport alternatives will increase the effect of road pricing.

Time-varying road pricing measures provide incentives to travellers to avoid more expensive periods and travel during cheaper periods. These time-varying road pricing measures may thus be effective to, for example, solve traffic problems. However, as traffic conditions improve, some travellers with a higher willingness to pay the charge may return to the peak. In order to adequately assess the departure time and route changes of travellers as results of changing time-dependent congestion patterns, we recommend that a dynamic network modelling framework is used to assess the potential network effects in the design process. Such a framework should include time dependent route choice and departure time choice of travellers when compared to a traditional static four-stage model. In the best case, all choice processes related to travel are explicitly modelled and feed-back mechanisms are in place to assess to effects of changing traffic conditions on the initially modelled choice behaviour.

In the Netherlands, a kilometre charging policy is now being designed which is to be differentiated by space, time and environmental characteristics of the vehicle. The objective is to create a fairer system of taxation compared to a lump sum system that exists now, charging travellers for the use of roads per kilometre. By introducing the before mentioned types of charge differentiation, it seems that such a system will do more than just charge for the use of roads, as it also charges more if the travellers impose greater costs on society by using their vehicles on the road they are travelling on at that time. Our recommendation, however, relates to how the effects of differentiation by time and space are assessed. Given our previous recommendation, we propose using a dynamic modelling framework for assessing these effects, opposite to the traditional static modelling framework i, which is known to be inadequate in assessing the changes in traffic conditions and models the route and departure time changes of travellers much more coarsely. More importantly, however, this modelling framework dictates the time windows of the differentiation, as fixed peak and off-peak periods are defined in the framework and the charge can only be differentiated by these three fixed periods. We recommend that modelling tools used for assessing the effects of road pricing measures never dictate how the measure is designed.

Future directions for research

In the research presented in this thesis, we focused on specific research interests and did not, for example, investigate the effect of secondary design dimensions on behavioural responses, nor did we look in detail at all the possible behavioural responses or system effects. There is

much more to investigate, even when maintaining our focus on the behavioural responses and network effects of time-varying road pricing measures. In this section, we will highlight a few of the future directions of research.

In modelling the behavioural responses towards road pricing, we have, in most of our models, treated our sample as if homogeneous, while we know the behaviour of commuters to be heterogeneous. We know from analyses of the respondents that they differ in socio-demographic backgrounds and in the travel conditions of their commute trips. In the models presented in this thesis, we only use the compensation of commute costs as a source of heterogeneity, but income, age, gender, etc. may further explain the heterogeneity in choice behaviour. We have done some analyses on explaining heterogeneity, for example in Van Amelsfort and Bliemer (2004), but not sufficiently to include results in this thesis yet. Ubbels (2006) has also estimated some choice modelling, including interactions of attributes with socio-demographics. We recommend that this research be continued and extended, not only by using approaches that explain heterogeneity with socio-demographics of respondents, but also using data on psychological constructs such as attitude, perceived behavioural control, personal norm, etc. that can explain heterogeneity. We have already done some analyses on this together with Linda Steg at the University of Groningen, but again not sufficiently to include it in this thesis, though a yet unpublished extended abstract has been submitted for the IATBR 2009 conference in India.

Related to further research in tackling heterogeneity, we recommend the estimation of other model types, more advanced than the MNL models we adopted in this thesis. For example, latent class models and panel mixed logit models may preferably be used to consider heterogeneity. In latent class models, different classes of respondents are created that show similar behavioural responses so that socio-demographic characteristics of respondents can then be used to analyse these classes separately. With panel mixed logit models, one not only can explain heterogeneity in choice behaviour, again using interactions between attributes and socio-demographic characteristics of respondents, but one can also estimate distributions of parameters rather than just the means. One can thus get a measure of unexplained heterogeneity as well. Another benefit of using the panel mixed logit model is that one can treat the answers of the respondents from the stated choice experiment as repeated choice from the same individual. We have estimated some of these models and found significant improvements in explanatory power (loglikelihood values shifting from around 15000 with MNL to 11000 with panel mixed logit). We also found that most of the unobserved heterogeneity can be found in road pricing, in congested travel time and in scheduling delay early parameters. These findings are preliminary and deserve more research and were thus not included in this thesis.

In order to conduct the research in this thesis, data were needed on the choice behaviour of individual travellers. These data were collected using a stated choice experiment among commuters who experience congestion on their home-to-work trip in the morning. This focus made the data collection efficient. However, in order to assess the network effects of road pricing comprehensively, we recommend the investigation of behavioural responses towards road pricing for other trip purposes as well, and the establishment of specific choice models for these trip purposes, similar to the commuter models derived in this thesis.

The model framework we developed in this thesis is already a complex and state-of-the-art framework, but it should still be further improved by, for example, taking into account travel time unreliability and junction delays on urban roads. In the analyses that we have conducted

so far using the modelling framework, we have only used choice models with linear sensitivities, although we have found strong evidence of non-linear sensitivities for some of the attributes in the utility functions. Possibly even more important is that we have, so far, used the model parameter values which resulted directly from estimations based on our sample. When the framework is applied to investigate the effects of road pricing in real applications, these parameter values will need to be re-estimated so that they become representative for the area of research. We would also recommend further research into the other behavioural responses towards road pricing so that the crude elastic demand model can be replaced by explicit models for mode, destination, trip frequency, and even car ownership choices.

Summary

Background

The transport of people and goods is important to the economic development of regions and nations. In most cases, the transport of individuals can be seen as derived demand, which means that the transport is not a purpose in itself, but a necessary means to engaging in an activity at another location. It is desirable that people engage in activities of their choosing, but the resulting demand for transport also has negative effects on society. Especially the significant growth in car traffic has negative effects such as environmental pollution, noise pollution, congestion, and less attractive public spaces. The challenge for governments is to manage mobility in a way that allows people to continue to engage in their desired activities while minimising the negative effects of transport. One of the potential policy options governments can use to manage mobility is road pricing.

This thesis addresses the problem of choosing appropriate road pricing measures from a traffic engineering perspective. This means that, given different policy objectives, we are interested in the behavioural responses of travellers and the resulting changes in the transportation network performance. The behavioural responses relate to travel decisions people make, like route and departure time choice. The network effects can, for example, be described by changes in flows and travel times on different roads. This traffic engineering perspective is important since most discussions about road pricing arise from a perceived lack of adequate transportation system performance.

Road pricing measures which are differentiated by time often have an underlying objective of reducing congestion. Congestion is however a complex phenomenon and thus we need detailed understanding on how travellers will change their behaviour and how these changes in behaviour affect the traffic conditions. Also, changes in traffic condition can again lead to further changes in behaviour. This research focuses precisely on these themes. In the Netherlands, but also internationally, there currently exists a lack in knowledge on both the behavioural responses and the network effects of specifically time-varying road pricing measures. The research consists of two parts. In the first part we focus on the behavioural responses of travellers and in the second part we used the behavioural models to construct a transport model that can forecast the network effects of time-varying road pricing.

Research findings

In this thesis we first established a new comprehensive stimulus-response framework that describes in detail how road pricing measures may affect the actions of individual travellers, how travellers may adjust their travel behaviour, and thus consequently affect the transport, economic and social systems. A wide gamut of potential reactions of different actors (individuals, households, companies, etc) is included in this framework. As a consequence of resulting changes in the transport system, further behavioural responses are considered. The stimulus-response framework firstly provides insights and an easy understanding of how road pricing directly and indirectly may affect individuals and the transport system.

Based on this framework, we then focus specifically on the elements related to behavioural and network effects of time-varying road pricing. In order to research the behavioural responses, and more specifically the departure time choice behaviour of commuters, a unique dedicated empirical data set has been established using a stated choice experiment we created. This stated choice experiment includes commuters' route, departure time, and mode shifts in response to time and place differentiation of road pricing stimuli. Additionally, the data include travel time unreliability as a traveller's choice attribute with a new way of operationalisation in order to better represent the unreliability experienced in real life. In the experiment we also better respect the repetitive nature of the commute trip by having respondents distribute a given number (10) of trips among alternatives instead of making a single choice. We demonstrated that respondents appear more sensitive to road pricing and are more likely to change departure times using this approach than we would have found using a traditional stated choice approach.

Using the data on choice behaviour of individual commuters we investigated and modelled the choice behaviour in detail. We examined how sensitive commuters are to the rescheduling of trips and we found that both departure time rescheduling and arrival time rescheduling are important in departure time choice of commuters, while traditionally only the arrival time rescheduling is included in models. We also found non-linear sensitivities towards rescheduling. The models show for example that commuters may not mind arriving somewhat later than preferred at work as long as they leave home at their preferred time. We also demonstrated that commuters may be able to adjust departure times only within limits and that rescheduling departure or arrival outside periods incurs further travel disutility upon the traveller. We conclude that departing late dominates choice behaviour of commuters, and this sensitivity increases with each extra minute of departing late. We also find, as other researchers, that commuters have a penalty for arriving too late, regardless of the amount of time that they are late. We constructed an example commuter, and when we apply the choice models to this example commuter we find that the scheduling penalties, especially for late scheduling, contribute so much to the total disutility, that realistic road pricing fees will only be a small component of disutility. This does not mean that road pricing will not affect behaviour when decision-makers compare alternatives.

We investigated the sensitivity of commuters to different types of costs and we find that commuters have unequal sensitivity towards fuel cost, road pricing charges and public transport cost. Commuters are most sensitive to road pricing costs and least sensitive to public transport costs. We also find that it is of key importance to take into account whether or not respondents are currently compensated for their commute costs by their employers. Respondents who are compensated are much less sensitive towards the road pricing fee than those who are not compensated. We expect that respondents who are currently receiving compensation for travel costs may expect to be compensated for road pricing fees as well. As

with rescheduling, we find that commuters have non-linear sensitivities towards fuel costs and road pricing fees. More specifically, we find that there is a lower sensitivity for extra charges above a charge of 4 euro. This means that the effectiveness of an extra euro in charges may decrease above a charge of 4 euro. In some of the models, we found a dummy for road pricing fee (=1 if road pricing exists) to be significant, implying that regardless of the road pricing fee, respondents associated extra disutility to alternatives that include road pricing. This may be explained and influenced by some of the secondary design dimensions of the road pricing measure.

Looking at the sensitivity of commuters towards different travel time components, we found that travellers are more sensitive towards congested travel conditions than free-flow travel conditions. This difference in sensitivity increases with higher travel times. Whereas in literature, the role of travel time unreliability has been tackled using either a mean-variance or a scheduling approach, we find that a combination of both performs better. While under some conditions, the two approaches have been shown to be identical, we found that a separate travel time unreliability parameter can be significant in a scheduling approach and the best results were found by not including travel time unreliability in a calculation of expected scheduling delays. We found that the sensitivity towards travel time unreliability is about half of the sensitivity towards travel time.

Using the different choice models, we designed and implemented a state-of-the-art, analytical, multi-user class dynamic equilibrium modelling framework which, apart from route choice, includes both departure time choice and elastic demand. This set of models allows for the forecasting of the network-wide travel and traffic impacts in response to a wide range of (time-varying) road pricing measures. The modelling framework has been shown to be feasibly applicable on large scale networks and we have applied it even within a road pricing optimisation framework (not covered in this thesis).

The modelling framework was applied on a real case in the Netherlands. Between Zoetermeer and The Hague a research program called “Spitsmijden” rewarded voluntary participants if they did not travel during peak hours. This negative road pricing measure had a significant impact on the departure time choice behaviour of participant, but as the number of participants was small, we investigated what the network effects could be if such a measure was implemented with increased levels of participation as well as with changing reward levels. We found that in this specific case the traffic conditions can both improve and deteriorate depending on the design of the measure. When high rewards levels are combined with high participation levels (and the expectation is that these two are correlated in reality), so many travellers will try to avoid the peak, that congestion starts earlier and as consequence conditions for the larger group of non-participants deteriorate. Although we did not find the precise optimal combination of participation level and reward level there seems to exist one. In that case enough participant adjust their behaviour to cause benefits for themselves as well as other travellers.

Societal implications

The results of this research shows that road pricing will lead to behavioural responses and that road pricing measures can be designed such that the intended behavioural responses are most likely to occur, including their subsequent changes in traffic conditions. Road pricing works and it will work as it was designed. We did, however, find that commuters are sensitive to rescheduling their home-to-work trips and that if changes in departure times are one of the intended behavioural responses, it is advisable to also implement additional measures that

make commuters less sensitive to rescheduling. We also found that commuters have different sensitivities towards different cost components, such as fuel costs and road pricing fees. This implies that aspects of a road pricing measure other than the price level will affect the changes in behaviour as well. It is important to investigate how other design dimensions of a road pricing measure can make the road pricing measure more effective rather than less effective. We showed that commuters who are compensated by their employer for commute costs are less sensitive to road pricing charges. It would increase the effectiveness of road pricing if employees were not compensated for this by employers.

Lastly, the model application for assessment of various reward schemes, showed that the complex interaction between the pricing measure, choice behaviour and traffic flow, can only be adequately assessed using dynamic models. This conclusion is not surprising, but until fairly recently only static models were capable of assessing effects in large scale networks. The road ahead is to further improve our forecast techniques using dynamic models and provide policy makers with better information in their decision-making processes. This research provides a step in that direction.

Dirk van Amelsfort

Samenvatting (summary in Dutch)

Achtergrond

Het vervoer van mensen en goederen is belangrijk voor de economische ontwikkeling van regio's en landen. In de meeste gevallen is het vervoer van personen een vorm van afgeleide vraag, dat wil zeggen, het vervoer is geen doel op zich, maar een noodzakelijk middel om een activiteit op een andere locatie te kunnen ondernemen. Het is wenselijk dat mensen de activiteiten van hun keuze kunnen ondernemen, maar de resulterende verplaatsingen hebben negatieve effecten op de samenleving. In het bijzonder de aanzienlijke groei van het autoverkeer heeft negatieve effecten, zoals milieuvervuiling, geluidshinder, congestie en minder aantrekkelijke, leefbare steden. De uitdaging voor veel beleidsmakers is om de mobiliteit op zo'n manier te faciliteren dat het voor mensen mogelijk blijft hun gewenste activiteiten te verrichten, terwijl de negatieve effecten van verkeer worden geminimaliseerd. Prijsbeleid is een van beleidsmaatregelen om dit te bereiken.

Dit proefschrift behandelt de ontwikkeling van prijsbeleid vanuit een verkeerskundig perspectief. Dit betekent dat, gezien de verschillende beleidsdoelstellingen, wij geïnteresseerd zijn in de gedragsreacties van reizigers en de daaruit voortvloeiende veranderingen in de verkeersafwikkeling. De gedragsreacties hebben betrekking op verplaatsingskeuzen die mensen maken, zoals route-, vervoerwijze-, en vertrektijdstipkeuze. De verkeerskundige effecten beschrijven we door de veranderingen in de stromen en reistijden op verschillende wegen en routes. Dit verkeerskundig perspectief is belangrijk aangezien de meeste discussies over prijsbeleid ontstaan vanuit gepercipieerde verkeersproblemen, en dan met name congestie.

Prijsmaatregelen waarvan de tarieven gedifferentieerd zijn naar verschillende tijdsperioden hebben vaak het doel om congestie te verminderen. Congestie is echter een complex fenomeen en om een differentiatie naar tijdsperioden goed in te kunnen zetten, hebben we in detail kennis nodig over hoe reizigers hun gedrag zullen veranderen en over hoe de gedragswijzigingen van individuen vervolgens doorwerken in de verkeersafwikkeling. Overigens hebben veranderingen in verkeersafwikkeling mogelijk ook weer een effect op gedrag. Dit onderzoek richt zich juist op deze thema's. In Nederland, maar ook internationaal,

is er relatief weinig kennis over zowel de gedragsreacties als de verkeerkundige effecten van tijdsgedifferentieerde prijsmaatregelen. Dit onderzoek bestaat globaal uit twee onderdelen; een onderdeel waarin we de gedragsreacties onderzoeken en modelleren en een onderdeel waarin we de gemodelleerde gedragsreacties gebruiken om verkeersafwikkeling te voorspellen gegeven een bepaalde prijsmaatregel.

De resultaten van het onderzoek

Om een goed inzicht te krijgen in hoe prijsmaatregelen van invloed kunnen zijn op de acties van individuele reizigers, en daarmee dus ook van invloed op verkeer en economische en sociale systemen, is eerst een stimulus-responsraamwerk ontwikkeld wat een breed gamma van mogelijke reacties van de verschillende actoren beschrijft. Het stimulus-responsraamwerk biedt een eenvoudig inzicht in hoe prijsmaatregelen direct, en indirect, van invloed kunnen zijn op het individu en het transportsysteem. Op basis van dit raamwerk hebben we ons vervolgens specifiek gericht op die elementen die betrekking op gedrags- en netwerkeffecten van tijdsgedifferentieerde prijsmaatregelen. Om de gedragsreacties te onderzoeken, meer specifiek de vertrektijdstipkeuze van forenzen, is een uniek stated choice experiment opgesteld. Uit dit experiment worden data verkregen over het route-, vertrektijdstip-, en vervoerwijzekeuze gedrag van forenzen in reactie op een naar tijd en plaats gedifferentieerde kilometerheffing. Het experiment is op twee manieren afwijkend van andere experimenten die in Nederland zijn uitgevoerd. Allereerst wordt in de keuze-alternatieven reistijdontrouwbaarheid meegenomen. Hiervoor is een nieuwe manier van presenteren gebruikt, in de vorm van een bandbreedte, die naar verwachting beter aansluit bij de onzekerheid die respondenten in het echt voelen als ze een vertrektijd moeten kiezen. Daarnaast hebben we in het experiment ook aandacht voor de repetitieve aard van woon-werkverkeerritten door de respondenten tien ritten te laten verdelen over de alternatieven in plaats van hen slechts een keuze te maken. Wij tonen aan dat de respondenten gevoeliger zijn voor prijsmaatregelen en hun vertrektijden meer aan zullen passen met deze aanpak dan we gevonden hadden met behulp van een traditionele aanpak.

De gegevens uit het experiment hebben we vervolgens gebruikt om het gedrag van forenzen te onderzoeken en te modelleren. We hebben onderzocht hoe gevoelig forenzen zijn voor veranderingen in vertrek- en aankomsttijden. Traditioneel wordt hierbij alleen naar de veranderingen in aankomsttijden gekeken, maar wij vinden dat zowel aanpassingen in vertrektijd als in aankomsttijd van belang zijn in het keuzegedrag. Verder vinden we ook niet-lineaire gevoeligheden ten aanzien van deze verschuivingen. We vinden bijvoorbeeld dat forenzen het minder erg vinden om te laat te komen op het werk, zolang ze maar op tijd zijn vertrokken. We hebben ook aangetoond dat forenzen hun vertrektijden en aankomsttijden alleen willen aanpassen binnen bepaalde grenzen en dat verschuivingen van vertrek- of aankomsttijd buiten deze perioden leidt tot extra disnut voor de reiziger. We kunnen concluderen dat te laat vertrekken het meeste disnut veroorzaakt voor forenzen en deze gevoeligheid neemt toe met elke extra minuut later vertrekken. We vinden, net als andere onderzoekers, dat forenzen disnut voelen voor te laat aankomen, ongeacht de hoeveelheid tijd dat ze te laat zijn. In de analyses van het gedrag van een hypothetische voorbeeldforens, vinden we bovendien dat de het disnut vooral voor te laat vertrekken en aankomen zoveel bijdragen aan het totale disnut dat realistische tarieven voor prijsmaatregelen slechts een klein deel van totale disnut zijn. Dit betekent niet dat een prijsmaatregel geen zal invloed hebben op het gedrag, aangezien het disnut veroorzaakt door een prijsmaatregel wel van doorslaggevend belang kan zijn in de vergelijking van keuze-alternatieven.

Aangezien ons onderzoek zich richt op prijsbeleid, hebben we ook onderzocht hoe gevoelig forenzen zijn voor verschillende soorten kosten. Wij vinden dat forenzen het meest gevoelig zijn voor de kosten van een prijsmaatregel, wat minder voor brandstofkosten en het minst gevoelig zijn ze voor openbaarvervoerkosten. Verder is het van essentieel belang om rekening te houden met eventuele compensatie van kosten van forenzen door hun werkgevers. Respondenten die aangeven nu compensatie te ontvangen zijn veel minder gevoelig voor de prijsmaatregel dan degenen die niet worden vergoed. We verwachten dat de respondenten die op dit moment een vergoeding ontvangen voor reiskosten, ook verwachten in de toekomst te worden vergoed voor heffingskosten van de prijsmaatregel. Ook ten aanzien van kosten hebben forenzen niet-lineaire gevoeligheden voor brandstofkosten en heffingskosten. Meer specifiek vinden we dat er sprake is van een lagere gevoeligheid voor extra kosten boven een heffing van 4 euro. Dit betekent dat de effectiviteit van een extra euro heffing minder wordt boven een heffing van 4 euro. In sommige van de modellen die we hebben geschat, is een dummy voor het bestaan van de prijsmaatregel significant (variabele is 1 als heffing bestaat). Dit impliceert dat ongeacht de hoogte van de heffing respondenten extra disnut toekennen aan de alternatieven waarin een heffing voorkomt. Dit kan mogelijk worden verklaard en worden beïnvloed door bepaalde secundaire kenmerken van de prijsmaatregel, zoals b.v. aanwending van opbrengsten, betaalsystemen en informatievoorziening.

Kijkend naar de gevoeligheid van forenzen voor verschillende reistijdcomponenten, dan zien we dat reizigers gevoeliger zijn voor reizen in congestie dan voor reizen onder congestievrije condities. Het verschil in gevoeligheid tussen de twee omstandigheden neemt toe met hogere reistijden. Ten aanzien van reistijdonbetrouwbaarheid vinden we dat modelspecificaties waarin onbetrouwbaarheid wordt beschouwd als een component van reistijd, en niet als een component van vertrek- en aankomsttijdaanpassing, het best presteert. We vonden dat de gevoeligheid voor reistijdonbetrouwbaarheid ongeveer de helft is van de gevoeligheid voor reistijd.

Gebruikmakend van de verschillende keuzemodellen die we hebben geschat, hebben we een verkeersmodel ontwikkeld en geïmplementeerd om de verkeerseffecten van prijsmaatregelen te kunnen voorspellen. Het gaat om een analytisch dynamisch evenwicht model met meerdere gebruikersklassen dat naast de standaard routekeuze ook vertrektijdstipkeuze omvat alsook een elastische vraag component. Het modelraamwerk is getest en toepasbaar op grote verkeersnetwerken. Alhoewel geen onderdeel van dit proefschrift is het modelraamwerk ook gebruikt binnen een optimalisatieroutine voor het vinden van de optimale heffingen (gedifferentieerd naar tijd en plaats).

Het modelraamwerk is ook toegepast in een onderzoek naar de potentiële effecten van beloningen voor het vermijden van de spits in Nederland. In het 'Spitsmijden'-project werden vrijwillige deelnemers beloond als zij niet in de spits met de auto van Zoetermeer naar Den Haag reisden. Deze negatieve prijsmaatregel had een aanzienlijke invloed op de vertrektijdstipkeuze van deelnemers, maar het aantal deelnemers was te klein om verbeteringen in de verkeerssituatie te veroorzaken. We onderzochten wat de verkeerseffecten zouden zijn indien een dergelijke maatregel wordt ingevoerd met meer deelnemers en met andere hoogtes van beloning. Wij vinden dat bij hoge beloningsniveaus gecombineerd met een hoge participatie (en onze verwachting is dat deze twee in werkelijkheid zijn gecorreleerd), zoveel reizigers de piek vermijden, dat congestie wat vroeger ontstaat dan normaal en als gevolg de verkeerssituatie wat verslechtert voor de grotere groep van niet-deelnemers die in de spits blijft rijden. Hoewel we de optimale combinatie van deelnameniveau en beloningsniveau niet exact vast hebben kunnen stellen, lijkt zo'n optimum

wel te bestaan, en ligt het optimum bij lagere participatiegraden en beloningshoogtes. In dat geval passen zoveel deelnemers hun gedrag aan zodat ze zowel voor zichzelf als voor de niet-deelnemers de situatie verbeteren.

Maatschappelijke implicaties

In de meest algemene zin blijkt uit de resultaten van dit onderzoek wederom dat prijsmaatregelen zullen leiden tot gedragsreacties. Verder zijn de richting en grootte van de gedragsreacties voorspelbaar alsook de veranderingen in verkeerscondities als gevolg daarvan. Dat maakt prijsbeleid ontwerpbaar. De modellen die zijn ontwikkeld in dit onderzoek dragen bij aan de verbetering van voorspellingen van effecten van prijsbeleid, met name van prijsmaatregelen met tijdgedifferentieerde heffingen. We hebben gevonden dat forenzen gevoelig voor vertrek- en aankomstaanpassingen van hun woon-werkrit en als wijzigingen in vertrektijden een van de belangrijkste beoogde gedragsreacties van een prijsmaatregel zijn, is het raadzaam om aanvullende maatregelen te treffen op gebied van mobiliteitsmanagement en (belasting)wetgeving om forenzen minder gevoelig te maken voor vertrektijdstipaanpassingen. We hebben ook geconstateerd dat forenzen verschillende gevoeligheden hebben ten aanzien van verschillende kostencomponenten. Dit impliceert dat andere aspecten dan de heffingshoogte ook van invloed zijn op gedrag en het is dus belangrijk om te onderzoeken hoe andere ontwerpaspecten van een prijsmaatregel de maatregel effectiever kunnen maken. Met name de manier en het moment waarop reizigers betalen zou hierbij groot verschil kunnen maken. Wij tonen aan dat forenzen die worden gecompenseerd door hun werkgever minder gevoelig voor heffingskosten. Het zou de effectiviteit van prijsmaatregelen vergroten als werknemers niet of minder werden gecompenseerd door werkgevers.

Tenslotte laat de modelstudie naar effecten van alternatieve beloningsregimes zien dat de complexe wisselwerking tussen een naar tijd en plaats gedifferentieerde prijsmaatregel, reizigersgedrag en verkeersafwikkeling alleen voldoende goed voor het nemen van de juiste beslissing, kan worden ingeschat met behulp van dynamische modellen. Deze conclusie is niet onverwacht, maar wel belangrijk, zeker in Nederland. Tot nu toe waren er slechts statische of semistatische modellen beschikbaar, maar de weg ligt open om het beter te doen en bestuurders betere informatie geven zodat zij betere beslissingen kunnen nemen. Uiteraard is meer onderzoek nodig.

Dirk van Amelsfort

Appendix A: examples of travel time unreliability in SP surveys



You have to be at your destination at 9:00

ITS

GREEN BUS
Fare on a single journey: £ 1.70

depart 8:22	depart 8:22	depart 8:22	depart 8:22	depart 8:22
arrive 8:59	arrive 9:00	arrive 9:00	arrive 8:59	arrive 9:01

RED BUS
Fare on a single journey: £ 0.80

depart 8:01	depart 8:01	depart 8:01	depart 8:01	depart 8:01
arrive 8:54	arrive 8:52	arrive 8:55	arrive 8:51	arrive 9:03

Which of these services would you prefer?

☐ GREEN BUS ☐ RED BUS

CONTINUE

Figure 1: Presentation of travel time unreliability as used by Hollander (2006)

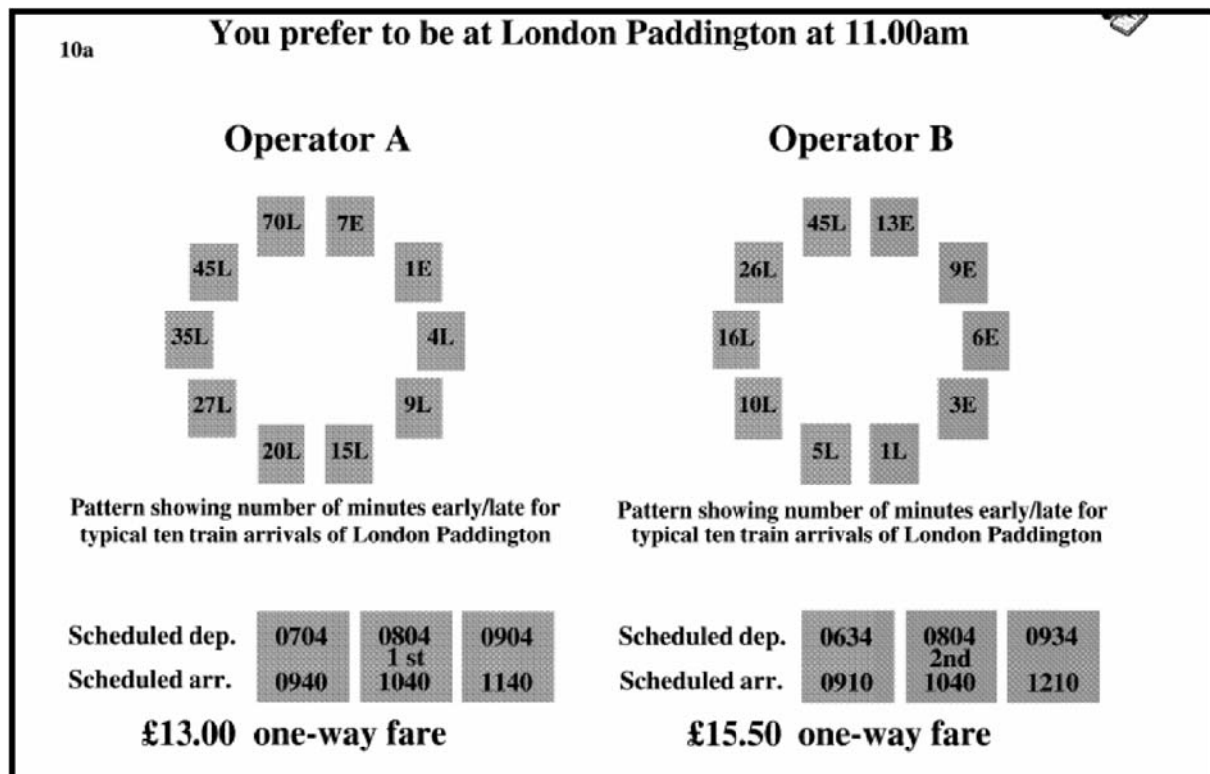


Figure 2: Presentation of travel time unreliability as used by Bates et al. (2001)

Appendix B: Triangular distribution of travel times

In this Appendix, some estimation results are presented of models that assume a triangular distribution of travel times. The peak of the distribution (c-parameter) in the models is used as the expected travel time attribute (this is not the mean of the distribution) and expected arrival time scheduling delays are calculated. The models are named M04_xx, where xx is the percentage of the travel time bandwidth that is used to set the peak of the distribution. So for M04_50, the peak is in the middle, for M04_10, the peak is almost equal to the minimum travel time and for M04_90, the peak is almost equal to the maximum travel time.

Table 9.3: Estimation results for models with triangular distribution of travel time (part 1)

Variable	M04_10		M04_20		M04_30		M04_40	
	Par	T-val	Par	T-val	Par	T-val	Par	T-val
Travelcost	-0.093	-16.26	-0.094	-16.52	-0.095	-16.61	-0.095	-16.62
E(TT)	-0.020	-17.92	-0.020	-17.81	-0.019	-17.68	-0.019	-17.66
E(asde)	-0.017	-18.29	-0.018	-18.22	-0.018	-18.08	-0.020	-18.09
E(asdl)	-0.036	-11.16	-0.030	-10.84	-0.023	-10.17	-0.020	-9.97
TTband	-0.009	-7.73	-0.011	-9.17	-0.012	-10.09	-0.012	-10.37
ASC_PT	-0.657	-6.68	-0.672	-6.82	-0.674	-6.84	-0.673	-6.83
TT_PT	-0.022	-17.47	-0.022	-17.42	-0.022	-17.38	-0.022	-17.38
Asde_PT	-0.019	-5.41	-0.019	-5.42	-0.020	-5.46	-0.020	-5.47
Asdl_PT	-0.013	-3.70	-0.013	-3.68	-0.013	-3.69	-0.013	-3.69
Log L	-15468		-15468		-15471		-15469	

Table 9.4: Estimation results for models with triangular distribution of travel time (part 2)

	M04_50		M04_60		M04_70		M04_80		M04_90	
	Par	T-val	Parer	T-val	Par	T-val	Par	T-val	Par	T-val
cost	-	-	-	-	-	-	-	-	-	-
	0.095	16.63	0.095	16.63	0.095	16,65	0,095	16,65	0,095	16,68
E(TT)	-	-	-	-	-	-	-	-	-	-
	0.019	17.65	0.019	17.64	0.019	17,64	0,019	17,63	0,019	17,56
E(asde)	-	-	-	-	-	-	-	-	-	-
	0.021	18.14	0.022	18.14	0.024	18,07	0,026	18,19	0,028	18,15
E(asdl)	-	-9.95	-	-9.97	-	-	-	-9,93	-	-
	0.017		0.015		0.014	10,00	0,013		0,012	10,02
TTband	-	-	-	-	-	-	-	-	-	-
	0.012	10.48	0.012	10.50	0.012	10,50	0,012	10,42	0,012	10,33
ASC_P	-	-6.83	-	-6.83	-	-6,84	-	-6,84	-	-6,88
T	0.672		0.672		0.673		0,673		0,676	
TT_PT	-	-	-	-	-	-	-	-	-	-
	0.022	17.38	0.022	17.38	0.022	17,39	0,022	17,37	0,022	17,34
AsdePT	-	-5.48	-	-5.49	-	-5,49	-	-5,50	-	-5,51
	0.020		0.020		0.020		0,020		0,020	
AsdlPT	-	-3.70	-	-3.70	-	-3,69	-	-3,69	-	-3,68
	0.013		0.013		0.013		0,013		0,013	
Log L		-15465		-15463		-15463		-15459		-15458

The development of loglikelihood values for the different modes indicates that the travel time that respondents took into account in their decision-making may not be the average travel time (middle of the bandwidth) but a much higher travel time or even the highest possible travel time. Looking at the parameter estimates of the different models, it seems that only the parameters of expected scheduling delays are changing. The chance of arriving early increases when taking into account higher travel times, and the sensitivity of expected arriving scheduling delay early does also. For expected scheduling delay late, the opposite is the case. In reality, the distribution of travel times is more likely to be skewed to the right than to the left, but people seem to mirror the distribution to determine an expected travel time.

About the Author

Dirk Hendrik van Amelsfort was born on the 1st of June 1974 in Schijndel, the Netherlands. After finishing a master in Civil Engineering at the Delft University of Technology in 2000, he joined Goudappel Coffeng. He started as a junior transport modeller but quickly he focussed on the development of models for both internal and external clients. As a result of his master thesis research into the I-15 Express Lanes in San Diego, USA, he became interested in road pricing and started his PhD research on this topic in 2002. Besides his PhD research on road pricing he has since then been involved in different research projects on road pricing, both in the Netherlands as for the European Union (CURACAO). Besides these research projects he was also project leader on projects dealing with toll roads in public-private settings. In these PPP projects he mainly worked for consortia of banks on both the equity and debt side of these infrastructure projects. In 2008 he became team leader of the new model innovation team (Tim) at Goudappel Coffeng. On the 1st of January 2009, however, Dirk moved to Sweden. Today he works at WSP Analysis & Strategy in Gothenburg.

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