Rewarding off-peak railway commuting: A choice experiment

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Abstract
Travelling by train is often considered as a possible alternative for commuting by car, to relieve extremely congested road networks. For this to be a solution to road congestion in the Netherlands, however, either train capacity during peak hours should be expanded or more current peak train passengers would have to be willing to travel during off peak hours. This paper considers the modelling of the departure time choice of Dutch train commuters and their willingness to reschedule their trip to off-peak hours when given a positive price incentive. In a conjoint choice experiment the scheduling costs of a large group of frequent train commuters is studied. The choice considerations of commuters in this setting are amenable to cross-nested logit and mixed logit estimations. The analysis shows that a positive price incentive can be an effective strategy and policy instrument to potentially increase the number of commuters travelling by train under a given capacity constraint. We show that the estimation of scheduling costs crucially depends on the way the scheduling choice of commuters is modelled within the discrete choice framework.

Keywords: Public transport, Schedule delay costs, Stated Preference Experiment, Discrete Choice Models

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1. Introduction

Consistent with the notion that an individual's choice for travelling should be considered as an attribute of that individual's activity pattern (see for example McNally and Rindt, 2008), Small (1982) introduced the concept of schedule delay costs for work trips. If a consumer wants to undertake certain activities during a day, he will schedule them according to his preferences, taking into consideration external constraints. Deviating from these scheduling preferences will result in disutility, i.e. schedule delay costs. Schedule delay costs is an important concept in the research focused on the alleviation of congested transport networks because they indicate the costs travellers attribute to changing their travel behaviour.

It is acknowledged that finding solutions to congestion on road networks includes the consideration of deploying other transport modes. When looking at work trips in the Dutch context, especially commuting by train is considered an alternative to commuting by car. Because capacity is nearly fully used during the peak, for this to be part of a solution to road congestion in the Netherlands, either train capacity during peak hours should be expanded or more current peak train passengers would have to be willing to travel during off-peak hours. The latter is furthermore an interesting proposition for railway companies to increase their sales under given capacity. In research on congestion of transport networks, the scheduling behaviour of railway commuters subject to price incentives is still an unexploited research area. More extensive knowledge on scheduling behaviour of railway commuters contributes to a better understanding of public transport use and might result in implications for demand-side congestion policies.

In order to study the travel behaviour of Dutch train commuters, a choice experiment was conducted by means of a stated preference questionnaire. Based on the scheduling costs and willingness to pay, we were able to study the choice considerations of Dutch train commuters. Due to the set-up of the questionnaire we could model the scheduling choices in different ways, and show that the ways the scheduling choices are specified within discrete choice models are crucial for determining the scheduling costs.

The remainder of this paper is set up as follows. Section 2 describes the set-up of the choice experiment. The data used for this paper is gathered for the 'Spitsmijden in het OV'[1] experiment. The data is analyzed using discrete choice models. A concise description of these models is given in section 3. Section 4 deals with the model specifications used to analyze the data. We applied cross-nested logit models to deal with substitution patterns across alternatives, and we applied mixed logit specifications to account for the repeated choice character of the survey. The results of our analyses are given in section 5. The last section concludes.

2. The choice experiment

In the summer of 2009, 1,421 commuters selected from the Dutch national railway (NS) company's consumer panel, participated in an online stated preference survey[2]. The commuters were selected for currently holding a pass for a specific route between 30-70 kilometres. The first part of the survey was set up to select participants who recently had commuted on average a minimal of 3 times a week during the morning peak hours (7:00h - 9:00h)[3] on a fixed route. In order to determine the preferred arrival time (PAT) and scheduling costs of the respondents, they had to give detailed departure and arrival time information concerning their commuting trips over a specific week, i.e. the reference week. In addition, travel and ticket information like class, monthly or yearly costs, route specifications, travelling comfort and preferences for travelling before or after the peak hours, was gathered.

In the project, a specific pass, i.e. the off-peak hours pass, was tested in a revealed preference experiment and also used in the specification of the stated preference experiment. That pass has the exact same features as the pass respondents are currently holding, except that it is not valid during a pre-indicated peak period and therefore is cheaper than their current pass. Only when combined with a peak supplement, a one-way specific ticket which travellers can buy on a daily basis, the off-peak hours pass is valid during peak hours. The decision to buy the new pass is therefore not an all or nothing decision, but the cost advantage reduces when a peak supplement is bought more frequently.

[1] Avoiding peak hours in public transport (Spitsmijden in het OV) is part of a broader research project 'Spitsmijden' aimed to study the possibilities in the Netherlands do deal with traffic congestion and subsequent externalities from a demand-side point of view.
[2] Response rate of 37%.
[3] Traveling during morning peak hours is defined as: being in the train during the time interval of 7:00h -9:00h or entering and/or leaving the train during the time interval of 7:00h - 9:00h.

Respondents were then asked about their preferences for keeping their current pass or purchasing the off-peak hours pass under different propositions. The propositions differ according to an orthogonal partial factorial design on the discount on the pass, the price of the peak supplement and the length of the peak period during which the off-peak hours pass is not valid. The factor design is given in table 1.

Table 1: Factor design stated preference-survey

Factor design	1st-class			2nd-class		
Price peak supplement (per day)	€2.50	€6	€9.50	€1.50	€3.50	€5.50
Discount (per month)	€50	€120		€30	€70	
Length peak period	7:00h-9:00h	7:30h-8:30h		7:00h-9:00h	7:30h-8:30h	

Because of the homogeneity in distance travelled, all respondents were presented with the same attributes that varied only by the class of their pass. In the Netherlands, travel expenses are generally fully or partly covered by the employer. This might weaken the impact of a price incentive on behaviour, both in real life and in a stated preference survey. Therefore, it is stated in the survey that the respondent should consider the discount to be hers, and the purchase of peak supplements then also occurs at one's own expenses. All respondents choosing the off-peak hours pass subsequently indicated how they would reschedule their commuting trips over a working week (number of days before, after or during the peak). Appendix A shows a choice screen for the stated preference experiment.

All respondents have been asked what their scheduling preferences are, would they not be able to commute during peak hours at all, i.e. the hypothetical scheduling question. With these answers, we could still analyse scheduling preferences even when the majority of the respondents would choose to keep their current pass in most situations presented and would choose not to change current behaviour (results show indeed 80% of the 4,278 choices would not change current behaviour). Qualitative analyses of the answers to both questions of the respondents that choose the off-peak hours pass, showed that the answers were quite consistent. Based on these observations, the hypothetical scheduling question is used for all respondents in estimating the behavioural models of what will below be called specification 1 and 2.

In order to calculate the preferred arrival time (PAT), the time that respondent usually arrives at work, reported departure and arrival times in the survey are compared to published train timetables. This allows us to consistently record trips made by the respondents. The trip selected from the timetable is the one which closest matches reported characteristics (changes, departure, and arrival). Only trips matching the reported number of changes and with scheduled departure and arrival within seven minutes of reported times are selected. In case of more than one timetable based trip matching these criteria, the one closest to reported times is withheld, using the square sum of time difference at departure and arrival as indicator (in case of equal rankings the difference at departure takes precedence). Reported trips not resulting in a match are excluded from the dataset.

The PAT is calculated as the arithmetic mean of the timetable arrival times of trips in the 7 to 9 am peak period (arrival after 7am and departure before 9am). Based on this PAT, the SDE is calculated for the latest possible trip before the start of the peak period (see $\text{arrival}_{\text{early}}$ in the utility functions (using train timetables)) and the SDL is calculated for the first possible trip after the peak period (see $\text{arrival}_{\text{late}}$ in the utility functions). Respondents exceeding the 30-70 kilometre interval were included in the dataset since estimates showed these observations to have little influence on the results.

3. Discrete choice models

The dataset is analyzed using discrete choice models. Discrete choice theory provides a broad range of modelling frameworks and modelling choice problems. The dataset used in this paper is amenable for different discrete choice specifications. Discrete choice theory models the probability that a consumer n chooses a given alternative j in choice situation[4] m as a function of the *random utility* U_{jmn} of the alternatives, expressed as:

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

where:

- V_{jmn} : the *deterministic part* of the utility for alternative j as obtained by consumer n in choice situation m —we will in this section assume that V_{jmn} is linear in parameters: $V_{jmn} = \beta' x_{jmn}$ with β a vector of coefficients and x_{jmn} a vector of decision variables relating to consumer n and alternative j in choice situation m;
- ε_{jmn} : the *stochastic part*.

The consumer then chooses the alternative with the highest utility (utility maximization).

[4] The index for choice situation m is introduced here to account for the repeated choice character of survey data.

In-depth discussions on discrete choice theory can be found in Anderson, Palma and Thisse (1992), Ben-Akiva and Lerman (1985), K. Train (1986/1990) and K. E. Train (2003). Here we briefly discuss the three main models within discrete choice theory; multinominal logit model, nested and cross nested logit models, and mixed logit model.

The *multinomial logit* model assumes a Gumbel distribution with variance $\sigma^2\pi^2/6$ for the stochastic utility ε_{jmn} . As we can see from expression above, any linear transformation does not affect the choice probabilities, as it does not affect the relative order of the alternatives' utility. This makes it impossible to identify the scale parameter σ of the stochastic part separately from the coefficients β of the deterministic part. In estimation the utility U_{jmn} is scaled by a factor $1/\sigma$, which normalises the variance of the stochastic part to $\pi^2/6$. The estimated coefficients $\hat{\beta}$ include the scale parameter σ of the stochastic utility:

$$\hat{\beta} = \frac{\beta}{\sigma}$$

The *nested multinomial* logit model extends the multinomial logit specification by allowing for correlation in unobserved preferences (stochastic utility) for a subset of alternatives. A partition structure defined by the researcher groups the alternatives in subdivisions or nests $S_1 \ldots\ldots\ldots\ldots S_K$. Based on Ben-Akiva and Lerman (1985) we define total utility U_{jmn} of alternative j in nest k as:[5]

$$U_{jmn} = V_{jmn} + \underbrace{\eta_{kmn} + \varepsilon_{jmn}}_{stochastic\ utility}$$

with:

- V_{jmn} the deterministic (observed) utility of alternative j;
- ε_{jmn} independent for all alternatives j, choice situations m and respondents n;
- η_{kmn} independent for all nests k, choice situations m and respondents n;

[5] The notation used here is equivalent to the more common notation where the stochastic utility $\eta_{kmn} + \varepsilon_{jmn}$ is represented by a vector of unobserved utility $\varepsilon_{mn} = \langle \varepsilon_{mn1} \ldots\ldots \varepsilon_{mnJ} \rangle$ which has a cumulative distribution $\exp\left(-\Sigma_{k=1}^{K}\left(\Sigma_{j\in S_k} e^{-\varepsilon_{mnj}/\lambda_k}\right)\right)$.

- ε_{jmn} iid Gumbel distributed with scale parameter λ_k;[6]
- η_{kmn} distributed so that $\max_{j\epsilon S_K}(U_{jmn})$ is Gumbel distributed with scale parameter σ normalized to unity.

For each nest k the parameter $\lambda_k (0 \leq \lambda_k \leq 1)$ is a measure for the correlation between the alternatives in nest k, with values closer to unity indicating less correlation. The choice probability P_{jmn} of alternative j (in nest k) in choice situation m by respondent n can in a nested logit specification be expressed as:

$$P_{jmn} = \frac{e^{\lambda_k I_{kmn}}}{\sum_{i=1}^{K} e^{\lambda_i I_{imn}}} \frac{e^{\widehat{\beta'} x_{jmn} / \lambda_k}}{e^{I_{kmn}}}$$

with I_{kmn} the inclusive value of nest k, defined as:

$$I_{kmn} = \ln \sum_{j\epsilon S_k} e^{V_{jmn} / \lambda_k}$$

In a *cross-nested logit* framework, each alternative j can be a member of more than one nest. An allocation parameter α_{jk} reflects the extent to which alternative j is a member of nest k. An alternative can be disproportionally allocated to different nests.

The *mixed logit* model is a further extension of the multinominal logit specification that provides a very flexible modeling framework. It defines the utility U_{jmn} as:

$$U_{jmn} = \beta' x_{jmn} + \underbrace{\eta_{jmn}{}' z_{jmn} + \varepsilon_{jmn}}_{stochastic\ utility}$$

with

- β a vector of fixed coefficients;
- η_{jmn} a vector of random terms probability distribution $f(\eta_{jmn})$, any distribution can be used (independence over j, m or n is *not* a necessary condition);

[6] In fact λ_k is defined as σ_k/σ with σ the scale parameter of $\max_{j\epsilon S_K}(U_{jmn})$ (here normalized to unity) and σ_k the scale parameter of ε_{jmn}.

- x_{jmn} and z_{jmn} vectors of observed variables;
- ε_{jmn} i.i.d. Gumbel distributed with scale parameter σ normalized to unity (independent over all alternatives j, choice situations m and respondents n).

In order to better understand the potential of the mixed logit specification to account for a repeated choice situation, we rewrite the utility formula as:

$$U_{jmn} = \alpha'^{x_{jmn}} + \eta_n' z_{jmn} + \varepsilon_{jmn}$$

with η_n a vector of random terms with mean zero which are independent for all respondents n (but constant over choice sets m). The error terms η_n introduce correlation between the utility U_{jmn} of alternatives j of the different choice sets m faced by the same respondent. All models described in this paper are estimated using the software package of Biogeme version 1.8 (Bierlaire 2003).

4. Model specifications

We used 3 different ways of specifying the scheduling costs that resulted in 3 utility specifications that we used for estimating the results. The set-up of the questionnaire was such that respondents could choose all possible commuting combinations within a three, four- or five-days-work-week: travelling with a normal peak pass; travelling before, during or after peak hours with an off-peak hour pass; or not travel at all (alternative). The different ways of specifying the utility functions in this analysis gives an interesting insight into the underestimation of scheduling costs if not all alternatives possible are considered. The three specifications we used are described below.

Specification 1

The utility specification that will be named specification 1, takes the most general specification of scheduling by defining seven utility functions based on the number of supplements bought per week (i , from 0 to 5) plus one for the alternative of travelling with the current pass:

$$U_{off-peak\ \ pass\ ,i} = \beta_{costs} * costs(i) + \beta_{sde} * sde(i) + \beta_{sdl} * sdl(i) + \beta_{discomf\ \_train} * discomf\_t(i)$$
$$U_{peak\ \ pass} = D_{no\ off-peak\ \ pass}$$

With:

- $U_{off-peak\ \ pass\ ,i}$ the utility of using the off-peak pass with *i* supplements;
- $i = 0, \dots \dots, 5$ the number of days per week the respondent buys a peak supplement;
- $U_{peak\ \ pass}$, the utility of using the current pass;
- costs, costs for buying supplements minus the discount of the off-peak pass per week (so negative if there is a cost advantage);
- *sde(i)*, schedule delay early per week;
- *sdl(i)*, schedule delay late per week ;
- discomf_t, expected number of days per week of travelling in a crowded coach (discomfort is only assumed to apply to travelling during peak hours and is based on the reported crowdedness in the reference week);
- $D_{no\ off-peak\ \ pass}$, alternative specific constant for keeping the current peak pass.

The calculation of *sde(i)* and *sdl(i)* is as follows:

$sde(i) = sde * (r - i) * before/(before + after)$

$sdl(i) = sdl * (r - i) * after/(before + after)$

With:

- $sde = \max(pat - arrival_{early}, 0)$;
- $sdl = \max(arrival_{late} - pat, 0)$;
- *r,* number of days commuting during the peak in the reference week;
- $i = 0, \dots \dots, 5$ the number of days per week the respondent buys a peak supplement;
- After, number of days a week travelling after peak hours;
- Before, number of days travelling before peak hours.

Each utility function then encompasses both scheduling early and scheduling late. In this specification, only the utility of the alternatives that are chosen are known because only the combinations of trips that respondents actually chose are considered. If we assume that a respondent chooses the trip that is the easiest or least costly, this would mean that only the scheduling costs for the 'easiest' trip choices are estimated in this specification. So if a respondent chooses to reschedule all his commuting trips to before the peak, we can estimate this utility, but not his utility for scheduling his trips to after the peak which is probably harder thus costlier for him. This would intuitively lead to underestimation of the costs of scheduling since the most difficult scheduling choices are not considered.

Specification 2

In utility specification 2, we also assume utility functions based on the number of supplements bought a week (*i* from 0 to 5) plus one for the alternative of travelling with the current pass. Additionally we assume that respondents would want to reschedule their trips based on a strict preference for travelling before or after peak hours. So the information given in the hypothetical scheduling question is used to assign to respondents a preference for either scheduling early or late. This is simply done based on the rule that the respondent chooses to reschedule to before peak hours if the number of days assigned to before peak hours is larger in the hypothetical scheduling question than the number of days assigned to after peak hours, and vice versa. Respondents choosing an equal number of days before and after are omitted from this estimation. This specification partly deals with the underestimation of scheduling costs by omitting all other possible scheduling combinations from the analysis and only focus on the scheduling of the most chosen, thus easiest scheduling choices . This specification has 12 utility functions:

$$U_{off-peak\ \ pass\ early,i} = \beta_{costs} * costs(i) + \beta_{sde} * sde(i) + \beta_{discomf\_train} * discomf\_t(i)$$
$$U_{off-peak\ \ pass\ late,i} = \beta_{costs} * costs(i) + \beta_{sdl} * sdl(i) + \beta_{discomf\_train} * discomf\_t(i)$$
$$U_{peak\ \ pass} = D_{no\ off-peak\ \ pass}$$

With:

- $U_{off-peak\ \ pass\ early,i}$ the utility of using the off-peak pass before the peak hours with *i* supplements;
- $U_{off-peak\ \ pass\ late,i}$ the utility of using the off-peak pass after the peak hours with *i* supplements;
- $U_{peak\ \ pass}$, the utility of using the current pass;
- $i = 0, \ldots\ldots, 5$ the number of days per week the respondent buys a peak supplement;
- costs, costs for buying supplements minus the discount of the off-peak pass per week (so negative if there is a cost advantage);

- *sde(i)*, schedule delay early per week;
- *sdl(i)*, schedule delay late per week ;
- *discomf_t*, expected number of days per week of travelling in a crowded coach (discomfort is only assumed to apply to travelling during peak hours and is based on the reported crowdedness in the reference week);
- $D_{no\ off-peak\ pass}$, alternative specific constant for keeping the current peak pass.

The calculation of *sde(i)* and *sdl(i)* is as follows:

$sde(i) = sde * (r - i)$

$sdl(i) = sdl * (r - i)$

With:

- $sde = \max(pat - arrival_{early}, 0)$;
- $sdl = \max(arrival_{late} - pat, 0)$;
- *r,* number of days commuting during the peak in the reference week;
- $i = 0, \ldots \ldots, 5$ the number of days per week the respondent buys a peak supplement.

When looking at the preferences for scheduling under the hypothetical scheduling question, the majority of the respondents indeed prefer to reschedule all their weakly trips to either before the peak or either after the peak. Only 17% of the choices for rescheduling work trips over a working week is some combination of rescheduling to travelling before and after peak hours.

Specification 3

Utility specification 3 actually deals with the problem of underestimation of scheduling costs by defining all utility functions possible in our research set-up. Each utility function is a combination of all possible weekly (5 working days) commuting trips. In total 57 utility functions are estimated based on combinations of travelling zero, one, two, three, four or five days a week, before (*b*), during (*d*) or after (*a*) peak hours with a normal peak hours pass or off-peak hours pass. In this utility specification, the possibility of an alternative (*o*) way of travelling (by car, bicycle, nor at all etc.) is introduced because the set-up of the questionnaire allowed for travelling less numbers of days when choosing the off-peak hours pass. The estimation in this model specification is not based on the hypothetical scheduling question but the actual answers in the choice experiment. The utility functions of specification 3 are:

$$U_{off-peak\ \ pass\ ,b,d,a,o}$$
$$= \beta_{costs} * costs(b,d,a) + \beta_{sde} * sde(b) + \beta_{sdl} * sdl(a) + \beta_{other} * other\ (o) + \beta_{discomf\ \_train} * discomf\_t(d)$$
$$U_{peak\ \ pass} = D_{no\ off-peak\ \ pass}$$

With:

- $U_{off-peak\ \ pass\ ,b,d,a,o}$ the utility of using the off-peak pass;
- $U_{peak\ \ pass}$, the utility of using the current pass;
- $\mathrm{b} = 0, \dots \dots, 5$ the number of days per week the respondent travels before peak hours;
- $\mathrm{d} = 0, \dots \dots, 5$ the number of days per week the respondent travels during the peak hours, i.e. buys a peak supplement;
- $\mathrm{a} = 0, \dots \dots, 5$ the number of days per week the respondent travels after peak hours;
- $\mathrm{o} = 0, \dots \dots, 5$ the number of days per week the respondent travels with an alternative mode or not at all;
- $b + d + a + o = 5$;
- costs, costs for buying supplements minus the discount of the off-peak pass per week (so negative if there is a cost advantage);
- $sde(b) = \left(\max\left(pat - arrival_{early}, 0\right)\right) * b$;
- $sdl(a) = (\max(arrival_{late} - pat, 0)) * a$;
- *discomf_t*, expected number of days per week of travelling in a crowded coach (discomfort is only assumed to apply to travelling during peak hours and is based on the reported crowdedness in the reference week);
- $D_{no\ off-peak\ \ pass}$, alternative specific constant for keeping the current peak pass.

It is helpful to notice that specification 2 is a subset of specification 3 since specification 2 encompasses those choices where all scheduling is either before or after the peak, which would, for example, be $U_{off-peak\ \ pass\ ,5,0,0,0}$ for someone rescheduling all commuting trips before the peak.

5. Results

We have estimated multinominal logit, cross-nested logit and mixed logit models with all three specifications, indicated with the suffixes A, B, and C respectively. In this section we will discuss the most relevant model estimations.

Multinominal logit

We have estimated a multinominal model with all three utility specifications. The results of these estimations, models 1A, 2A and 3A, are given in table 2. All coefficients are significantly different from zero at the 1%-level and have the expected sign, except for the utility of discomfort in model 1A and 2A. We would have expected that the congestion in the train coach would negatively influence utility, even if a passenger has a high possibility of sitting himself. We have also run estimations with coefficients on self discomfort (possibility of having no seat), but these estimations are mostly insignificant. We must note however that comfort in the estimation is based on the reported comfort during the reference week and might therefore suffer from endogeneity.

The most basic logit models are able to explain a fair part of variance in railway commuter behaviour, with a minimum ρ^2 of 0.603. Models 2A and 3A support the idea that commuters tend to have less disutility from arriving early than from arriving late. Table 3 gives the value of schedule delay for arriving early and late. The values in model 1A indeed indicate that this model specification underestimates the scheduling costs because only the 'easiest' scheduling is reflected in the estimations. The difference in estimated scheduling costs between model specifications 2A and 3A are striking. The main difference between both model specifications is the variety of scheduling combinations specified, so the explanation of the difference in values must be related to the scheduling possibilities. As is stated in section 4, part of the explanation is that only the easiest scheduling choices are represented in model specification 2. The other part of the explanation might be that in model specification 2, the discerning impact of scheduling early or late on the utility of respondents is lower than in model specification 3.

Table 2: estimated results

Explanatory variables	1A (multinominal logit model)	2A (multinominal logit model)	2C (mixed-logit model)	3A (multinominal logit model)	3B (cross-nested logit model)	3C (mixed-logit model)
β_{sde} (hour/week)	-0.440** (-11.91)	-0.503** (-14.20)	-0.659** (-9.29)	-0.741** (-18.58)	-0.525** (-16.98)	-1.40** (-10.28)
β_{sdl} (hour/week)	-0.363** (-9.98)	-0.642** (-16.57)	-0.811** (-10.11)	-0.905** (-21.58)	-0.742** (-11.62)	-1.26** (-10.35)
β_{costs} (€/week)	-0.146** (-26.34)	-0.157** (-27.38)	-0.231** (-20.84)	-0.153** (-26.30)	-0.125** (-23.54)	-0.173** (-19.14)
$\beta_{discomfort\_train}$	0.0777** (2.62)	0.138** (4.54)	0.159* (2.44)	-0.110** (-3.54)	-0.0495* (-2.06)	-0.0531 (-0.60)
β_{other}				-3.55** (-10.86)	-2.61** (-7.31)	-6.56** (-8.66)
$D_{no\ off-peak\ pass}$ [σ^2]	3.57** (-53.33)	3.96 ** (56.55)	5.46** [6.51] (28.30)	3.74** (52.70)	2.84** (41.18)	3.83** (27.84)
λ_{other}†					0.735** (2.91)	
λ_{after}†					0.826 (1.63)	
λ_{during}†					0.202* (2.46)	
λ_{before}†					0.341** (6.78)	
Other [σ^2]						-2.52**[6.36] (-8.97)
After [σ^2]						-0.829** [0.687] (-4.20)
During [σ^2]						-0.622** [0.387] (-5.20)
Before [σ^2]						0.326 [0.106] (1.33)
Parameters	5	5	6	6	10	10
No. of observations	4,215	4,059	4,059	4,215	4,215	4215
No. of individuals	4,215	4,059	708	4,215	4,215	721
No. of Halton draws			32,000			36,000
Null log-likelihood	-7853.951	-9873.431	-9873.431	-16043.658	-16043.658	-16043.658
Final log-likelihood	-3119.021	-3276.299	-2924.264	-3838.821	-3706.344	-3217.400
ρ^2	0.603	0.668	0.704	0.761	0.769	0.799

Robust t-values in parenthesis. Significance indicated by ** and * referring to the 1% and 5% level respectively. †The reported coefficient is 1/ λ and significance is calculated against H_0 : λ=1, H_1: λ<1.

The intuition behind this reasoning is that the marginal utility of scheduling costs will get closer to zero the more our way of modelling scheduling costs deviates from the way respondents perceive this attribute. This results in lower scheduling costs in model specification 2.

The positive coefficient for the alternative specific constant indicates that, all other things equal, commuters get positive utility from keeping their current pass. Model 3A includes a coefficient concerned with the utility of alternative choices like not travelling or travelling by car. The coefficient for this variable also shows a disutility for deviating from the normal travel pattern, all other things equal. A different explanation might also apply to this variable. If, in the reference week, people travel, for example, 5 times a week during peak hours, and indicate in the stated choice that they will travel only 4 times a week, this can also be a mistake made by the respondent.

Table 3: Value of schedule delay

Payment vehicle	Model 1A	Model 2A	Model 2C	Model 3A	Model 3B	Model 3C†
SDE (€/h)	3.01 (0.28)	3.20 (0.25)	2.85 (0.34)	4.84 (0.32)	4.20 (0.31)	*8.09* *(0.89)*
SDL (€/h)	2.49 (0.27)	4.09 (0.29)	3.51 (0.39)	5.92 (0.36)	5.94 (0.57)	*7.28* *(0.80)*

Standard error of the ratio in parenthesis: standard errors calculated based on the robust standard errors of the estimated coefficients according to common calculus of standard errors. †The values of these ratios should be interpreted with care because the accuracy of this estimation is questioned.

Though not reported in this paper, we have tested for socio-economic and demographic interaction variables on the monetary or time attributes in the models, but have found no clear patterns. Only very weak results are found for the level of income. The general pattern being that the value of schedule delay early is lower and the value of schedule delay late is higher for respondents with a higher income than those with a lower income.

Cross-nested logit model

Given the nature of the choices that respondents had to make in this experiment, a cross-nested logit model is estimated for model specification 3 assigning alternatives to 4 nests: travelling *before, during,* or *after* peak hours or some *other* choice. The utility function for the current peak pass is assigned to a different nest, that was fixed to one (no correlation across alternatives in a nest) and is not reported in table 2. We used a cross-nested specification because we consider it plausible that substitution patterns between alternatives are correlated and thus disproportional. Someone travelling five times a week after peak hours is more likely to switch to travelling four times after peak hours than to travelling four times before peak hours. The set up of specification 3 allows for estimating this hypothesis. The allocation parameter is set based on the value of *b,d,a* and *o* in the utility functions in specification 3: if $b = 0$, $\alpha = 0\%$; if $b = 1$, $\alpha = 20\%$; if $b = 2$, $\alpha = 40\%$; if $b = 3$, $\alpha = 60\%$, if $b = 4$, $\alpha = 80\%$; if $b = 5$, $\alpha = 100\%$ with the sum of alpha's being equal to 1. So if someone indicates that he will travel 3 days per week before and 2 days per week after peak hours, he will be allocated to the before nests for 60% and to the after nest for 40% and is more likely to substitute between these nests. The model is estimated with fixed allocation values.

The result of this estimation, model 3B, is given in table 2. We see a small but significant improvement in the fit of the model as compared to estimation 3A. All the estimated coefficients have the expected sign and are all significantly different from zero at the 1%-level, expect for the coefficient of discomfort which is significant at the 5%-level. The scheduling costs found ,are €/h 4.20 (SDE) and €/h 5.94 (SDL), again indicating that respondents get more disutility from arriving late. All other things equal, commuters get a positive utility from keeping their current pass. In this model we find a significant though small negative impact of discomfort in the train on utility.

The parameter λ_k is tested against the null hypothesis of no correlation between alternatives in nest *k*, $\lambda_k = 1$, and rejected for the hypothesis that $\lambda_k < 1$, meaning that substitution between alternatives within nest *k* is higher than substitution between alternatives in other nests. The null hypothesis is rejected for all nests expect for the *after* nest. Correlation is highest within the nest of travelling during peak hours with peak supplements and travelling before peak hours. We interpret this result as stating that the choices in nest *during* have the most variance between choices across unobserved variables.

Mixed logit model

To account for unobserved correlation between the choices of individual respondents in the dataset, we turn to estimating mixed logit models with model specifications 2 and 3. The results are given in table 2. Model 2C and 3C account for the panel structure in our dataset. Model 2C assumes that coefficient $D_{no\ off-peak\ pass}$ is constant and normally distributed over choices made by the same respondent. $D_{no\ off-peak\ pass}$ is highly significant with a variance of 6.51 confirming correlation of unobserved heterogeneity. The other coefficient estimations in this model are all highly significant and have the expected sign, except for the discomfort coefficient which is positive and significant at the 5%-level. The fit of this specification is significantly better in the panel structure than in the multinominal logit estimation in model 2A. We have found a value of schedule delay of €/h 2.85 (SDE) and €/h 3.51 (SDL).

Model 3C accounts for a panel structure by imposing that the coefficient for nests are constant and normally distributed over choices made by the same respondent. The fit of this model is significantly better than models 3A and 3B, reaching a ρ^2 of 0.799.We are not confident about the accuracy of this model though, because estimates showed that the t-values differ significantly with the number of draws. More elaboration on this model specification is needed in further research with better numerical tools.

6. Conclusion

The most conclusive estimates in this paper are models 2C and 3B. We have found that the specifications of the utility functions are crucial for determining the scheduling costs. Model specifications in which either only the 'easiest' scheduling choices are accounted for, or the calculation of scheduling costs deviates too much from the way respondents perceive it, will likely underestimate the scheduling costs. All other things equal, commuters attribute a positive utility to their current travel behaviour, but a group of commuters is willing to travel during off-peak hours when given a positive price incentive; the values of schedule delay are between €4.20 (SDE) and €5.94 (SDL). It seems that respondents differ much in taste and personal preferences, which are not accounted for in the model. In the cross-nested logit model specification we clearly found that the probability of choosing one alternative is not independent of irrelevant alternatives. We did not find a very convincing relation between comfort in the train coach and the choice considerations of commuters for travelling during or off-peak hours.

7. References

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Appendix A.

Choice screen stated preference questionnaire:

You usually commute *5 days* a week between *Utrecht and The Hague*. The Dutch railway company offers you the following tickets for these trips:

A. A *monthly* season pass for the route *Utrecht-The Hague* for *€360*.
B. An off-peak *monthly* season pass for the route *Utrecht-The Hague* for ***€330***. This pass gives you a discount of **€30** compared with option A, however, you are not allowed to travel with this pass from Monday to Friday between **7:00h-9:00h** unless you buy a peak supplement of **€3.50** per day.

Which pass would you purchase?

- ○ A
- ○ B

If you choose pass B:

Could you indicate when and how often you would commute during your *5-day working week* now that you have purchased an off-peak *monthly* season pass not valid between **7:00h-9:00h**?:

I would commute …… days a week before the peak
I would commute …… days a week after the peak
I would commute …… days a week during the peak and buy a peak supplement of **€3.50** a piece.

note: attributes of the choice set are indicated in bold letters. Attributes of the individual respondent are indicated in italic letters.