Behavioural responses to PAYD: an empirical stated choice study in the Netherlands

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1 Introduction to PAYD

The insurance costs for a car are considerable. A Dutch car owner pays on average about €500 a year for his insurance. An amount comparable with the yearly fixed car taxation costs (MRB) and about half of the yearly fuel costs for an average driver in the Netherlands (Vonk, Janse, van Essen and Dings, 2003). At present these insurance costs are paid periodically, and are in most cases independent of the number of kilometres driven or related in a very coarse way only. The increased risk of involvement in an accident when driving more kilometres is hardly incorporated in the price to be paid. This also means that motorists typically do not perceive insurance cost savings when they reduce kilometrage.

Over recent years there has been increasing attention for a new car-insurance system where costs are not fixed anymore but instead depend on driver behaviour. One of the most obvious behavioural dimensions is the number of kilometres driven, since risks generally increase with usage. Some (pilot) initiatives have already been implemented where such a *pay as you drive* insurances (PAYD) are offered to customers (e.g. Atlanta (U.S.) and Houston (U.S.)). Most of these systems encompass a simple replacement of fixed premiums by a more variable system where insurance premiums depend on the number of kilometres driven.

Technological possibilities, however, nowadays allow for a more advanced system with differentiated charges, possibly affecting many more behavioural dimensions than kilometrage alone. These developments are closely followed by insurance companies. A system that changes traffic behaviour, preventing accidents and reducing severity of these accidents, is interesting to insurers, as it obviously leads to a reduction in size and number of future claims. For instance, insurers may want to discourage driving at roads with a higher risk. This calls for a system where the level of the premium is related to the level of risk per driven kilometre.

There is an extensive literature devoted to the analysis of traffic accidents and crash modelling, the majority of which deals primarily with the analysis of crash involvement and prediction of crash totals (Delen, Sharda and Bessonov, 2006). Understanding the circumstances under which drivers and passengers are more likely to be killed or more severely injured in a car accident can help improve the overall driving safety situation.

Factors that affect the risk of increased injury of occupants in the event of an accident include demographic or behavioural characteristics of the person (age, gender, seatbelt usage, or use of drugs or alcohol while driving), environmental factors and roadway conditions at the time of the accident occurrence (surface, weather or light conditions, the direction of impact, vehicle roll, or occurrence of a rollover), as well as technical characteristics of the vehicle itself (age and body type) (Delen et al., 2006).[1] Also driving speed, in combination with speed limits and traffic density at roads, appears to be an important factor in road safety (Aarts and van Schagen, 2006). A number of studies have attempted to develop injury severity models, though most concentrate on the traffic accident records limited to a small geographic area, a particular accident type (e.g. fatal accidents for which ample data sets are available), or a certain road condition situation.

In this paper we will study if and how a differentiated insurance premium can influence driving behaviour with respect to speeding, distance driven, road type chosen and transport mode. We will discuss the design and implementation of a conjoint choice experiment. For the analysis of the observations collected in the experiment we use discrete choice theory to estimate a series of choice model specifications.

2 The choice experiment

2.1 Context

The conjoint choice experiment reported in this paper was conducted as part of a larger PAYD research project that also involved a real world experiment where part of the insurance premium was specified as a function of actual driving behaviour. In this paper we will limit ourselves to findings of the stated preference choice experiment.

Starting in January 2007, the project recruited approximately 250 participants to the trial between customers with age between 18 and 26 years from five Dutch insurance companies. After recruitment the participants had to complete a participation survey in March 2007.

The survey discussed in this paper was completed by all participants to the real world experiment during Summer 2007, and before their participation to the trial started (January 2008). It was clearly indicated that their responses to the survey would not affect the level of their insurance premium.

The survey that carried the conjoint choice experiment also included questions collecting information for other behavioural analyses. We will limit our discussion here to the choice experiment that made up the first part of the survey.

The choice experiment was implemented in the format of a web based survey, and the participants were invited by email to complete it.

2.2 Survey design

The experiment is set up around the choice between different travel alternatives for a given trip, including both route choice and modal choice. In order to make the choice as realistic as possible, a couple of introductory questions deliver information on actual travel behaviour, which is subsequently used to customise the presented choice sets.

The participation survey already completed by the participants asked for the share of trip purposes in weekly mileage, specified as education, commuting/business, visiting

[1] For clarity we note that these variables may influence both the probability that an accident happens and the damage level in case an accident happens.

relatives, and other purposes. Based on the reported shares, a trip purpose was selected on which the remainder of the choice experiment focused.[2]

The participant is first asked to specify some characteristics of the last (domestic) trip for the selected trip purpose. One is the length of this trip, which will be further referred to as d. We also ask the duration t of this trip. A next characteristic of the trip is the main road type used. The respondent has a choice between urban roads (for $d < 15$km), non-urban roads (for all values of d) and motorways (for $d \geq 15$km).

Finally a representative fuel mileage is asked for, as well as the fuel type used. An option is offered to report fuel mileage as unknown by the participant, in which case an average fuel efficiency is used in calculations of the relevant attributes for the respondent. Unrealistic values of fuel mileage are replaced with average values as well. The selected mileage together with prevailing fuel prices at the time of the experiment determine per kilometre fuel costs C_F.

The car trips presented in the choice set are specified to have an insurance coverage identical to the existing coverage reported by the participant in the first participation survey.

After the introductory questions the participant is presented with nine choice sets. Each choice set included four travel alternatives: two car trips, one public transport trip and one choice alternative representing transport modes other than car or public transport as well as the option not to travel.

The presented trip alternatives are specified as being fully characterised by the presented attributes. The private car trips are customised using the reported trip length d and travel duration t, and are described using the following attributes:[3]

- main road type r: one alternative using non-urban roads (for all values of d) and the other alternative using urban roads (for $d < 15$km) or motorways (for $d \geq 15$km)
- fuel cost $C_{F,r}$ and distance d_r, with d_r for each road type alternative r varying across three levels around the reported $d \pm 20\%$ according to a factorial plan (see below)
- travel duration t_r: for the reported road type a base value is determined by the reported travel duration corrected for d_r compared to d, for the alternative road type a base value is determined using a factor of 1,5 (and correcting for d_r compared to d), the presented value varies at three levels around the base value ±20% according to a factorial plan
- insurance cost $C_{I,r}$: for each alternative a base value is calculated corresponding to €0,04d_r, variation around this value is at three levels according to a factorial plan with a bandwidth corresponding to the variation in fuel price $C_{F,r}$
- speeding s_r: for each car trip alternative speeding is described according to the factorial plan as either "strict", at least one speed limit infringement with less than 15km/h, or at least one infringement with more than 15km/h

The public transport alternatives are described by:

- ticket cost C_{PT}: to determine a value for ticket cost a (non-revealed) distance d_{PT} is calculated identical as for the road alternatives (including 20% variation

[2] A trip purpose was selected at random with a probability proportionally to the reported shares. Trip purposes with a reported share lower than half of the country-wide average were excluded from the selection mechanism.

[3] For the calculation of presented fuel costs, insurance costs, travel duration and ticket costs the reported trip length d is first validated against travel duration t and corrected accordingly where implied average speed fell outside a realistic range for the reported road type.

at three levels), next the ticket price is set to €$0,5+0,06 d_{PT}$ (loosely based on average ticket revenues reported by public transport operators in the Netherlands)

- travel duration t_{PT}: a base value for travel duration (in minutes) is determined as $60/(0{,}3+16/d_{PT})$, next variation is introduced around this base value with 20% according to a factorial plan

The *other* alternative does not have any attributes associated with it.

To avoid order related bias, the alternatives and attributes are randomised across respondents (but kept constant across choice sets faced by the same respondent).

The levels of the attributes were set according to an underlying D-efficient fractional factorial design. Two designs were developed, one for $d < 15$km and another one for $d \geq 15$km.

An example of a choice set is included in appendix.[4]

3 Analysing the stated preferences

In this section we will proceed to a behavioural analysis based on the stated preference data collected in our conjoint choice experiment. Our analysis will apply discrete choice theory, which we will first briefly introduce.

3.1 Discrete choice theory

Discrete choice theory provides a broad range of modelling frameworks. An in-depth discussion on discrete choice theory can be found in Anderson, Palma and Thisse (1992); Ben-Akiva and Lerman (1985); K. Train (1986/1990); K. E. Train (2003).

Discrete choice theory models the probability that a consumer n chooses a given alternative j in choice situation[5] m as a function of the *random utility* U_{jmn} of the alternatives, expressed as:

$$U_{jmn} = V_{jmn} + \varepsilon_{jmn} \tag{1}$$

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 maximisation).

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 (1), 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 utility ε_{jmn} 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

[4] Note that the original survey was established in Dutch, which has been translated to English for the purpose of this paper.

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

of the stochastic part to $\pi^2/6$. The estimated coefficients $\hat{\beta}$ include the scale parameter σ of the stochastic utility:

$$\hat{\beta} = \beta/\sigma \tag{2}$$

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 $S_1 \dots S_K$. Based on Ben-Akiva and Lerman (1985) we define total utility U_{jmn} of alternative j in nest k as:[6]

$$U_{jmn} = V_{jmn} + \underbrace{\eta_{kmn} + \varepsilon_{jmn}}_{\text{stochastic utility}} \tag{3}$$

with:

- V_{jmn} the deterministic (observed) utility of alternative j for respondent n in choice situation m;
- 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;
- ε_{jmn} iid Gumbel distributed with scale parameter λ_k;[7]
- η_{kmn} distributed so that $\max_{j \in S_k}(U_{jmn})$ is Gumbel distributed with scale parameter σ normalised to unity.

For each nest k the parameter λ_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:

$$P_{jmn} = \frac{e^{\lambda_k I_{kmn}}}{\sum_{i=1}^{K} e^{\lambda_i I_{imn}}} \frac{e^{\hat{\beta}' x_{jmn}/\lambda_k}}{e^{I_{kmn}}} \tag{4}$$

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

$$I_{kmn} = \ln \sum_{j \in S_k} e^{V_{jmn}/\lambda_k} \tag{5}$$

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

$$U_{jmn} = \beta' x_{jmn} + \underbrace{\eta_{jmn}' z_{jmn} + \varepsilon_{jmn}}_{\text{stochastic utility}} \tag{6}$$

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] 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 $\varepsilon_{mn} = \langle \varepsilon_{mn1}, \dots, \varepsilon_{mnJ} \rangle$ which has a cumulative distribution $\exp\left(-\sum_{k=1}^{K}\left(\sum_{j \in S_k} e^{-\varepsilon_{mnj}/\lambda_k}\right)\right)$.

[7] In fact λ_k is defined as σ_k/σ with σ the scale parameter of $\max_{j \in S_k}(U_{jmn})$ (here normalised 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 normalised 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 (6) as:

$$U_{jmn} = \alpha' x_{jmn} + \eta_n' z_{jmn} + \varepsilon_{jmn} \tag{7}$$

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.

3.2 Multinomial logit

In our analysis of the observations we want to study how respondents trade off different attributes of the trip alternatives. We start with a simple multinomial logit specification with a linear utility function.

Because there is a potential issue here as the average level of most attributes correlates by design with the respondent specific distance d, we divide these attributes by d before they enter the utility formulas, so that we are effectively modelling utility per kilometre:[8]

$$\begin{cases} U_r = \alpha_F C_{F,r}/d + \alpha_I C_{I,r}/d + \beta_C t_r/d + \gamma_{\leq 15} s_{\leq 15,r} + \gamma_{>15} s_{>15,r} + \delta_r + \varepsilon \\ U_{PT} = \alpha_{PT} C_{PT}/d + \beta_{PT} t_{PT}/d + \delta_{PT} + \varepsilon \\ U_O = \delta_O + \varepsilon \end{cases} \tag{8}$$

with

- r the road type (urban, non-urban or motorway)
- U_r the utility of car alternative using road type r
- U_{PT} the utility of the public transport alternative
- U_O the utility of the generic other alternative
- $C_{F,r}$ fuel costs of car alternative using road type r
- C_{PT} ticket costs of public transport alternative
- $C_{I,r}$ insurance cost of car alternative using road type r
- t_r travel duration of car alternative using road type r
- t_{PT} travel duration of public transport alternative
- $s_{\leq 15,r}$ a dummy variable[9] identifying minor speeding (less than 15km/h above the speed limit) of car alternative using road type r
- $s_{>15,r}$ a dummy variable identifying major speeding (more than 15km/h above the speed limit) of car alternative using road type r
- all greek letters are coefficients to be estimated (α monetary, β travel duration, γ speeding and δ alternative specific constants)
- ε the random utility

To allow for estimation of the set of coefficients, we need to fix arbitrarily one alternative specific constant to zero. We decided to choose $\delta_{\text{nonurban}} = 0$. All estimations

[8] Alternative specific dummy variables have been omitted from these alternative specific utility formulas and their coefficients δ are represented as alternative specific constants.

[9] A dummy is a variable whose value is 1 when the represented characteristic is present and 0 otherwise.

reported here and in the subsequent section are conducted using a beta version of Biogeme 1.9 (Bierlaire, 2003).

The results of the estimation are reported in table 1. We note that the coefficients all have the expected sign. All coefficients are significantly different from zero, with the exception of the public transport ticket price coefficient and the alternative specific constant for the urban road type.

As one would expect from actual car drivers, the public transport alternative has a negative alternative specific constant. Even the travel duration coefficients for both alternatives (β_C and β_{PT}) express a smaller disutility from a minute travelling by car compared to public transport. Everything else equal, drivers do like motorways over all other road types.

For the values of speeding, we note that everything else equal (including travel duration) increased speeding is valued more negatively. That is an expected finding under the assumption of risk neutral behaviour, but it needs to be mentioned that socially expected behaviour may be an explanation as well, provided that this was an insurance-themed experiment.

The valuation of insurance premium α_I does not depart significantly from the valuation of fuel costs α_F. The valuation of ticket price α_{PT} proved not significantly different from zero, probably a result of the limited number of observations in which the public transport choice alternative was selected (about 4%) as well as the variation in ticket price (in €/km) across the choice sets being rather small.

The travel duration valuation implied by the travel duration coefficients β and monetary coefficients α is presented in table 4. We will discuss them at the end of the mixed logit section.

We did estimate a couple of alternative specifications, where we tested for differentiated coefficients along a number of dimensions. If we exclude drivers that do not bear the costs of travelling themselves (this information is available from the survey), the estimated coefficients do not draw a different picture. Furthermore, estimating separate cost or travel duration coefficients for short ($d < 15$km) versus long trips ($d \geq 15$km) does not reveal differences in behaviour as a function of trip distances. Finally, estimating separate travel duration coefficients for each road type results in estimates that are also not significantly different.

Table 1: Multinomial logit estimation (log-likelihood: −1861,759, adjusted rho-square: 0,390)

			robust statistics		
coefficient	attribute	value	std err	t-test	p-val
α_{PT}	ticket price in €/km	0,527	1,77	0,30	0,77
α_F	fuel cost in €/km	−8,61	1,79	−4,81	0,00
α_I	insurance cost in €/km	−10,8	1,75	−6,21	0,00
β_{PT}	travel duration in min/km	−1,28	0,139	−9,18	0,00
β_C	travel duration in min/km	−0,583	0,0782	−7,45	0,00
$\gamma_{\leq 15}$	minor speeding dummy	−0,579	0,0859	−6,74	0,00
$\gamma_{>15}$	major speeding dummy	−1,02	0,0854	−11,98	0,00
δ_{urban}	urban road dummy	0,126	0,0967	1,31	0,19
δ_{motorway}	motorway road dummy	0,779	0,0716	10,88	0,00
δ_{PT}	public transport dummy	−2,02	0,307	−6,57	0,00
δ_O	*other* alternative dummy	−4,82	0,248	−19,48	0,00

3.3 Nested logit

A second modelling specification tested for is the nested logit model, which allows for correlation in unobserved preferences for different alternatives (in the same choice set).

The setup of our choice sets covers both mode choice and route choice (for the private car transport mode). It is to be expected that unobserved preferences for the car alternatives correlate, hence we define a nesting structure where the car alternatives share a nest.

The resulting model coefficients are presented in table 2. The nesting structure proves significant (λ different from 1), which means that substitution between car alternatives is larger compared to modal substitution.

Otherwise, the most important difference with the multinomial logit model (table 1) is that the coefficient δ_{urban} of the urban road dummy is now significant.

The increase in model fit (expressed by the log-likelihood statistic) is rather small. An explanation may be that correlation should not be modelled at the individual choice but at the level of the individual respondent (hence by accounting for correlation between choices by the same respondent). Nested logit does not allow for such a specification, this is why we move on to mixed logit modelling in the next section.

3.4 Panel mixed logit

The mixed logit model specification allows for arbitrarily distributed model coefficients. In this application we define a normally distributed alternative specific coefficient for the car alternatives δ_C with mean zero and estimate its standard deviation. The coefficient is defined to be constant over choices made by the same respondent. As such, we mimic the correlation pattern of the nested logit estimation in a panel specification.

The resulting model parameters are presented in table 3. We see an important improvement in model fit over the previous two specifications, which is a clear indication towards the panel specification of correlation in unobserved heterogeneity.

The coefficients of fuel costs α_F and insurance costs α_I are now nearly identical, confirming the analysis in the multinomial and nested logit specifications where they

Table 2: Nested logit estimation (log-likelihood: −1852,059, adjusted rho-square: 0,393)

			robust statistics		
coefficient	attribute	value	std err	t-test	p-val
α_{PT}	ticket price in €/km	1,29	1,62	0,80	0,42
α_F	fuel cost in €/km	−5,94	1,41	−4,22	0,00
α_I	insurance cost in €/km	−6,57	1,38	−4,77	0,00
β_{PT}	travel duration in min/km	−1,19	0,137	−8,68	0,00
β_C	travel duration in min/km	−0,491	0,0715	−6,87	0,00
$\gamma_{\leq 15}$	minor speeding dummy	−0,344	0,0739	−4,65	0,00
$\gamma_{>15}$	major speeding dummy	−0,633	0,0965	−6,56	0,00
δ_{urban}	urban road dummy	0,163	0,0636	2,57	0,01
δ_{motorway}	motorway dummy	0,419	0,0824	5,09	0,00
δ_{PT}	public transport dummy	−1,88	0,269	−7,00	0,00
δ_O	*other* alternative dummy	−4,30	0,218	−19,77	0,00
$1/\lambda$	inclusive value of car nest	1,73	0,232	3,15	0,00

Table 3: Mixed logit estimation (8000 Halton draws, log-likelihood: −1658,558, adjusted rho-square: 0,456)

coefficient	attribute	value	robust statistics std err	*t*-test	*p*-val
α_{PT}	ticket price in €/km	−1,05	4,17	−0,25	0,80
α_F	fuel cost in €/km	−11,3	2,95	−3,84	0,00
α_I	insurance cost in €/km	−11,0	1,82	−6,03	0,00
β_{PT}	travel duration in min/km	−1,50	0,302	−4,99	0,00
β_C	travel duration in min/km	−0,846	0,179	−4,72	0,00
$\gamma_{\leq 15}$	minor speeding dummy	−0,646	0,133	−4,87	0,00
$\gamma_{>15}$	major speeding dummy	−1,13	0,131	−8,61	0,00
δ_{urban}	urban road dummy	0,297	0,169	1,76	0,08
δ_{motorway}	motorway dummy	0,715	0,117	6,13	0,00
δ_{PT}	public transport dummy	−4,26	0,693	−6,15	0,00
δ_O	*other* alternative dummy	−7,97	0,558	−14,27	0,00
stdev(δ_C)	private car dummy	−3,09	0,333	−9,30	0,00

had already been identified as not differing significantly. It reveals that the respondents do not attach any specific preferences to paying a variable insurance premium compared to fuel costs which have traditionally been variable. Also the value of the other coefficients largely confirms the multinomial and nested logit estimations.

The travel duration valuation can be calculated as the ratio of the travel duration coefficients β to the monetary coefficients α. Provided that we did not find significant monetary coefficient values for public transport, we limit our discussion to private cars trips (table 4). The calculated valuations[10] do not differ significantly across model specifications or monetary coefficients. The obtained values are generally lower than what is typically presented in literature (Jong and Tegge, 1998).

4 Conclusion

This paper discusses the design of a conjoint choice experiment to analyse the impact of differentiated PAYD insurance schemes. A number of choice models are estimated. The behavioural analysis identifies the trade off of different safety related indicators to insurance cost. The implied travel duration valuations are realistic.

[10]The presented standard errors of the coefficient ratios are calculated using classical rules of error calculus. An alternative approach would be to estimate the valuation directly on the observation dataset using a non-linear deterministic utility specification (value of time space estimation) where the corresponding standard errors would follow directly from the model estimation.

Table 4: Travel duration valuations for private car trips

model specification	travel time valuation in €/h fuel cost (std err)	insurance cost (std err)
multinomial logit (table 1)	4,06 (1,01)	3,24 (0,68)
nested logit (table 2)	4,96 (1,38)	4,48 (1,15)
mixed logit (table 3)	4,49 (1,51)	4,61 (1,24)

The simple observation that car drivers trade off the different choice variables rationally implies that a differentiated insurance premium constitutes an effective policy instrument for increasing traffic safety. We did not find a significant difference between the impact of per kilometre insurance cost and fuel cost. The policy instrument of fuel taxation has however the drawback that it does not allow for much differentiation and moreover can the user compensate higher tax levels by increasing fuel efficiency.

In the analysis of the survey observations we found that young drivers generally disapprove of unsafe behaviour. Both with respect to speeding and choice of route type did we observe that the safer alternatives are preferred ceteris paribus.

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Choice set example

Imagine there are four travel alternatives for the education purpose trip that you described. These alternatives are represented in the table below. Also imagine that these alternatives do really exist. The alternatives only differ in the characteristics presented in the table, including trip specific insurance cost. This premium substitutes for the annual premium which is cancelled.

	Trip A	**Trip B**	**Trip C**	**Trip D**
fuel cost	€1,45 (10km)		€1,45 (10km)	ticket: €1,20
transport mode	private car	other mode than private car or PT, or cancelling the trip	private car	public transport
route	along roads outside built-up areas		along roads inside built-up areas	
speed: do you exceed the speed limit	at least one infringement of the speed limit with 15 km/h or less		at least one infringement of the speed limit with 15 km/h or less	
travel duration (door to door)	10min		15min	37min
insurance cost	€0,70		€0,40	

Each column in the table above represents a fictitious travel alternative. Which of the above trips (A, B, C or D) do you prefer most and would you most likely chose in reality? Imagine that all other circumstances (appointments, occupations) are identical to the day when you made the trip that you described.