The influence of panel effects and inertia on travel cost elasticities for car use and public transport

Lissy La Paix^{1,2} · Abu Toasin Oakil³ · Frank Hofman⁴ · Karst Geurs¹

Accepted: 11 June 2021 / Published online: 27 August 2021
© The Author(s) 2021

Abstract

Studies on the impact of changes in travel costs on car and public transport use are typically based on cross-sectional travel survey data or time series analysis and do not capture intrapersonal variation in travel patterns, which can result in biased cost elasticities. This paper examines the influence of panel effects and inertia in travel behaviour on travel cost sensitiveness, based on four waves of the Mobility Panel for the Netherlands (comprising around 90,000 trips). This paper analyses the *monetary* costs of travel. Panel effects reflect (within wave) intrapersonal variations in mode choice, based on three-day trip diary data available for each wave. The impact of intrapersonal variation on cost sensitiveness is shown by comparing mode choice models with panel effects (mixed logit mode choice models with error components) and without panel effects (multinomial logit models). Inertia represents variability in mode choice between waves, measured as the effect of mode choice decisions made in a previous wave on the decisions made in the current wave. Additionally, all mode choice models include socio-economic and spatial variables but also mode preferences and life events. The effect of inertia on travel cost elasticities is measured by estimating mixed logit mode choice models with and without inertia effects. The main conclusion is that the inclusion of intrapersonal effects tends to increase cost sensitiveness whereas the inclusion of inertia effects decreases travel cost sensitiveness for car and public transport modes. Car users are identified as inert travellers, whereas public transport users show a lower tendency to maintain their usual mode choice. This paper reveals the inertia effects over four waves of repeated respondent's data repeated yearly.

Keywords Inertia effects · Hybrid choice modelling · Longitudinal data · Mobility Panel Netherlands

✉ Lissy La Paix
llapaix@pevidahighwaydesigners.com

¹ Department of Civil Engineering, University of Twente, Drienerlolaan 5, 7522 NB Enschede, The Netherlands

² Pevida Highway Designers, LLC., Miami, Florida, United States

³ DAT.Mobility, Snipperlingsdijk 4, 7417 BJ Deventer, The Netherlands

⁴ Rijkswaterstaat WVL, P.O. Box 2232, 3500 GE Utrecht, The Netherlands

Introduction

Our grasp of people's travel behaviour is still mostly based on cross-sectional surveys in which only one day is surveyed for each respondent, often also limited to representative periods with maximal traffic flows (see for an overview Ortúzar 2011). Although cross-sectional surveys give relevant information about travel patterns at a particular moment, it is difficult to ascertain how choices will vary over time (i.e. policy response) if the system changes (Yáñez et al. 2010). Studies on the impact of changes in travel costs on car and public transport use are typically based on cross-sectional travel survey data or time series analysis and do not capture intrapersonal variation in travel patterns, which can result in biased cost elasticities. This paper analyses the *monetary* costs of travel, being the other inconveniences of a trip considered *impedances*, in general.

Also, the influence of habits, giving rise to inertia effect, has been discussed in the travel behaviour literature since the 1980s (e.g., see for overviews Cherchi and Manca (2011); van Exel (2011)). Inertia refers to the tendency that the outcome of a previous choice affects the present choice. Cantillo et al. (2007) developed inertia models, which were later extended by Yáñez et al. (2010). Similarly, González et al. (2017) analysed positive and negative inertia in mode choice with revealed preference (RP) and stated preference (SP) data, based on a mixed logit model formulation. Cherchi et al. (2013) used hybrid choice models to represent inertia by measuring the tendency to stick with the same alternative (inertia) via lagged variables. Those variables linked the current choice with the previous trip(s) made for the same purpose, during the same time of day, and with the same mode of transport. Other studies have estimated inertia effects over SP data or combinations of RP/SP data (Cantillo et al. 2007; Cherchi and Manca 2011; González et al. 2017), or analyzed data collected over repeated waves, but corresponding to smaller samples (Yáñez et al. 2009) or reduced samples of continuous panels, e.g. continuous panel six weeks of a small sample (Cherchi et al. (2013). For an overview of unrepeated versus repeated panel surveys see for example Thomas et al. (2019).

Similarly, Cherchi et al. (2017) used panel data to account for day-to-day and week-to-week variability in mode choice and found more variability in mode choice across weeks than across days of each week. Further, La Paix Puello et al. (2017) showed that intrapersonal trip rates vary significantly by year, by week, and by day of the week. At this point, trip rates refer to the number of trips per person-day collected. Ignoring the heterogeneity in individual travel behaviour can lead to misrepresentations in mode choice models, and the greater an individual's number of choices is, the stronger this *bias* becomes. It means that the inertia of users concerning certain modes (e.g. car users) might also be related to their frequency of use of other modes. For example, car users who (occasionally) use a bicycle are more likely to switch to the bicycle; see Kroesen (2014) and de Haas et al. (2018). However, the extent to which a previous choice increases (or decreases) the utility of both subsequent and multiple choices over time is still unclear. To overcome this

gap, the present paper analyses a repeated sample of respondents over four waves of data repeated yearly.

Few papers in the literature have examined the impact of inertia on the cost sensitivity of travel. Some studies that used pseudo panel data revealed, particularly concerning elasticities of travel costs, that inertia effects are stronger in the short term than in the long run (Dargay 2004). Recently, Yang and Timmermans (2014, 2015) analysed consumer response to fuel price fluctuations with the aid of GPS panel data for the Netherlands. The results showed a significant degree of inertia of car use in response to increased fuel prices.

This paper aims to improve the measurement of the travel cost changes on mode choice by calculating travel cost elasticities with and without inertia effects, controlling for neighborhood accessibility variables and life events. To our knowledge, a model that estimates inertia effects on long-run panel data (multiple days and years over the same sample) with a large sample of stayers is unprecedented in the literature.

In our paper we are utilising a unique panel data set, i.e. the Mobility Panel of the Netherlands (MPN) (Hoogendoorn-Lanser et al. (2015)). This firstly allows us to capture inertia and panel effects. We use the term inertia to represent variability in mode choice between waves, measured as the effect of mode choice decisions made in a previous wave on the decisions made in the current wave. Secondly, the MPN allows us to capture the impact of life events on inertia in travel cost elasticities. We examine three life-events, which were the most significant for mode choice: start a job, get a new job, and childbirth (Oakil et al 2016). This unique combination of information on life-changing moments and (changes in) travel behaviour enables us to study the relationship between inertia and life events related to mode choice decisions.¹

We use the term *panel effects* representing the day-to-day variability in travel patterns, based on three-day trip diary data available for each wave. Other studies considered lagged variables to represent inertia as indicators of latent measurements, see for example Cherchi et al. (2013). Cherchi and Cirillo (2010) used the number of times that the same tour has been made in previous days of the same week as a measure of the “strength” of habit. The advantage of our approach is the inclusion of unobserved effects via the difference in utility, which covers any unobserved effect between waves. Whereas a lagged variable would only account for the effects related to the measurement of that variable or the combination of indicators.

Finally, variability of travelers mode choice in decision making process has been extensively investigated from different theories and perspectives applied to route choice models, such as Instance-Based Learning -IBL- (e.g. Tang et al 2017) and cumulative prospect theory -CPT- e.g. (Jou and Chen (2013), Yang et al. (2017), Yang and Jian (2014), Ghader et al. (2019)). The present paper is based on the utility maximization theory applied to mode choice modeling, even though CBT and IBL have received most recent attention. The advantage of using the utility maximization theory relies on the reported information instead of the “recalled” information as Instance Based Learning (IBL) or CPT. Similarly, in our model the decisions are weighted by the simulation embedded in the mixed logit model, as it will be discussed in “Analytical framework: inertia and hybrid choice model” section.

The remainder of this paper is structured as follows. “Data source, enrichment, and description” section describes the data used in the choice modelling analysis. “Analytical

¹ We use the term *inertia* to represent variability in mode choice between waves, measured as the effect of mode choice decisions made in a previous wave on the decisions made in the current wave.

framework: inertia and hybrid choice model” section presents the hybrid choice modelling framework. “Model results” section describes the results of the estimated models; “Model implementation: point elasticities” section covers forecasting and elasticities. Finally, “Conclusions and discussion” section presents the conclusions and discussion.

Data source, enrichment, and description

Data source

As mentioned in “Introduction” section, we used data from the four waves of the Mobility Panel of the Netherlands’ database to conduct this study. The Mobility Panel of the Netherlands (in Dutch: ‘MobiliteitsPanel Nederland’ or MPN) is the world’s largest ongoing. It was initiated by the Netherlands Institute for Transport Policy Analysis (‘KiM’), the University of Twente, and Goudappel Coffeng to be able to identify and explain day-to-day variations in mobility and the role of habits in travel behaviour (Hoogendoorn-Lanser et al. 2015). It consists of a state-of-the-art web-based three-day mobility diary, a household survey, and a personal survey. It contains approximately 6,000 respondents in around 2,500 households, from whom data has been collected since 2013. Furthermore, it includes 1,978 households in which all members completed both the individual questionnaire and the travel diary. This makes it possible to analyse travel behaviour at the individual level as well as at the household level.

Analysis is conducted for four waves of travel data (2013–2016) on work and non-work activities. As for non-work activities, the MPN considers trips for purposes such as picking up people or goods, shopping (grocery and non-grocery), tours (including walking), hobbies (e.g. sports), leisure activities, and accessing personal care services. For each trip, the MPN survey collected origin, destination (postcode level), reported distance, chosen modes, travel time, starting time of the trip, ending time of the trip, parking costs, and delays.

The first dataset was collected in the period from August to November 2013; 3,572 households participated in this wave, 6,126 persons completed the questionnaire and nearly 4,000 people filled out a three-day travel diary. The dataset includes various personal characteristics such as age, gender, education, and employment status, as well as the mobility of these respondents. Respondents are also asked about the occurrence of life events related to their work situation (for example changing job, change of working hours, change of work location) and household situation (for example childbirth, start living together, moving home). Around 2,000 of the respondents were stayers, people who also participated in one or more of the following waves.

Table 1 shows a summary of consecutive and inconsecutive stayers in the database. As we can observe, there were 1,247 consecutive stayers divided over 937 households. Of these households, about 70% was both single-person households and households composed by adults with younger kids, while 25% of the households consisted of two people and rest 4% had three or more people in the household. Since most of the households were single-person households, we expected an analysis at the individual level to yield the best model output. The sample for the model estimation is composed by 4256 individuals, which is the total number of respondents who participated in two (2) waves or more.

Table 1 Number of respondents in the MPN panel 2013–2016

Number of waves	Waves	No. of respondents with questionnaires	No. of respondents with questionnaires and diaries
1	1	1342	478
	2	2421	577
	3	153	23
	4	2368	1278
2	1 and 2	1155	211
	1 and 3	159	26
	1 and 4	4	0
	2 and 3	740	260
	2 and 4	222	95
	3 and 4	100	35
3	1, 2 and 3	926	270
	1, 2 and 4	129	61
	1, 3 and 4	71	31
	2, 3 and 4	1560	760
4	1, 2, 3 and 4	2340	1247

Data enrichment

The availability of a rich travel information database provides opportunities for enriching the data with alternative-specific information. In this case, the possibility existed to enrich the data with travel mode-specific information such as travel distance, travel time, and travel cost. Although the respondents reported the travel time and distance for their chosen travel mode, travel distance, and time data for non-chosen alternatives could be derived from the origin and destination information of a trip. In the MPN, the origin and destination of each trip are known at the 6-digit postcode level, which is information at street level, or even sections of streets. Using route-planning software, the network distance and travel time can be calculated for each origin–destination pair for each travel mode. However, the information was not always complete. Due to missing values for either origin, destination, or both at the 6-digit postcode, we did not have the travel distance or travel time for about 10% of the total number of trips by car or public transport. Therefore, these trips were excluded from the data. Among the reported trips, travel distances and travel times were missing for about 15% of the bicycle trips, and for trips made on foot. In those cases, we calculated the distance over the network, and we derived walking or cycling times by using average walking and cycling speeds, respectively. Since reported travel times do neither represent actual nor perceived travel times truthfully (Peer et al. 2014) we enriched the information of the non-chosen alternatives instead of replicating the self-reported information. See Appendix A for a comparison between self-reported and calculated travel times.

The MPN does not include any self-reported information on travel cost, but travel costs can be estimated with the aid of other variables (license plate of vehicles, public transport cards). Car travel costs are based on fuel efficiency and fuel price. The Dutch Road Authority ('RDW') records the fuel type and efficiency of each registered car in the Netherlands and the MPN recorded the car registration number and the main user of each car. Based on

Table 2 Average monthly Fuel Prices over the three years of the sampled data

Year	Month	Benzine Euro95 (€/lt)	Diesel (€/lt)	LPG(€/lt)
2013	9	1.758	1.437	0.716
2013	10	1.7	1.406	0.716
2013	11	1.677	1.387	0.724
2014	9	1.728	1.415	0.762
2014	10	1.681	1.374	0.75
2014	11	1.632	1.358	0.709
2015	9	1.511	1.191	0.57
2015	10	1.481	1.184	0.588
2015	11	1.507	1.192	0.612
2016	9	1.491	1.149	0.556
2016	10	1.517	1.193	0.58
2016	11	1.501	1.186	0.596

these two sources of information, we were able to derive the travel cost for each car trip by the user. We assumed that the main user always uses his or her car, even if there are more cars available at the household level, and that all household members use the same car if only one car is available in the household. We ignored the possibility that people may use other vehicles. For the travel cost by train, we used the kilometer price given by Dutch Railways ('NS'). BTM travel cost was derived from regional transport fare listings for the Netherlands. Table 2 shows the average fuel prices over the three waves of the mobility data. The car costs were assigned based on the type of car available in the household.

Data description

For this study, we focused the data description on the distribution of travel mode choices over three different categories of explanatory variables, namely (i) socioeconomic characteristics, ii) mobility resources (car ownership and driving license), and (ii) urbanisation level. The data we used represent a sample from all four waves that are currently in the MPN database. After the exclusion of non-responses and observations with missing attributes for non-chosen alternatives, the final sample contained about 90,000 trips. Appendix C shows the distributions of travel mode choices over different socioeconomic characteristics. We chose gender, age, education, and personal income as important socioeconomic characteristics to describe the data and the sample distribution. We can make the following general observations:

- In the age group between 40 to 50 years, people are most likely to use a car.
- Men are more likely than women to drive a car and women prefer to cycle more often than men.
- There is a positive relationship between income and driving a car and a negative one between income and public transport use. However, cycling is a more complex behaviour, which is influenced by several other factors as age, route, origin–destination, and others.

In addition, we investigated travel mode choice in relation to availability of driving licence and personal car ownership. As we expected, people who own a car were more likely to choose the car and people with no car were more likely to cycle; see Appendix C. Residential location plays an important role in travel mode choice. The level of urbanisation is defined based on density of addresses (per km²) by Statistics Netherlands ('CBS'). Appendix C shows a table summary of the sample characteristics. We can observe that the share of car trips in mode choice is, as expected, higher in less urbanised areas than in highly-urbanised areas. BTM is the least chosen travel mode except in highly urbanised areas.

Analytical framework: inertia and hybrid choice model

A mixed logit model is implemented to disentangle both panel and inertia effects. Mixed logit models are widely known by the ability to represent correlations across respondents (intrapersonal variation) and temporal effects (inertia). More specifically, temporal effects relate to the influence of decisions previously made. Figure 1 shows the choice model framework we used; the discrete choice model (DCM) is shown on the left, and the inertia (*I*) effects are shown on the right, with the corresponding measurement equations. Inertia was accounted for by letting the indirect utility functions of the alternatives of the choice situation at time *t* depend on the outcome of the choice made at a previous point in time *t-1*. Therefore, we developed three (types of) models:

- M1: A standard multinomial logit
- M2: Standard mixed logit model with error components that capture panel effects given by multiple observations of the same individual.
- M3: Inertia model, consisting of a mixed logit model—M2—with inertia effects.

As can be seen in Fig. 1, two types of equations are required in this approach: *dashed arrows* link the *unobservable effects* (e.g. *inertia*) to its observable indicator. As implemented by Gonzalez et al. (2007), the inertia effect is expressed as a function of the past perceptions of the transport modes made by the individuals at a previous choice situation (difference in utilities). The arrows connecting both utilities and inertia mean that when the individual evaluates the alternative *j* in the current situation *t*, it also considers the utility that the alternatives *j* had in the previous situation *t-1*. A *structural equation* (solid arrows) links the observed measurement of inertia effects and *mode choice* model. For both choice and inertia models, disturbances are represented by dashed-dotted arrows. Explanatory variables related to socioeconomic factors, travel-related characteristics (including cost and time), life events, preferences, and neighbourhood descriptors were added to the DCM only. Figure 1 shows that the discrete choice part is composed of mode choice and inertia effects.

Discrete choice model

The discrete choice model was developed for mode choice, based on the following alternatives: car driver, car passenger, BTM, train, cycling, and walking. The unit of analysis is the trip level. The choice model, in this case, U_{jn} , is the utility faced by individual *n*, taking *j* mode (choice) of transport:

Fig. 1 Modelling framework

$$U_{jn}^t = ASC_j + \sum_l \beta^s SE_n + \sum_r \beta^z Z_n + \sum_m \beta^M M_n + \sum_d^{LE} \beta^{LE} LE_n + \beta_j^{LOS} LOS_{jn}^t + \mu_{jn} + \varepsilon_{jn} \quad (1)$$

where the utility function is expressed as a function of a vector of socioeconomic and survey characteristics (SE_n) with size l , and mode preferences M_n with vector size m of individual n with vector size m as well as a vector of neighbourhood characteristics (Z_n) with vector size r ; t means the time (e.g. trip or day of survey). LE is the vector of variables associated with the life events, with a vector size d ; β_j^{LOS} is the vector of parameters associated with the level of service (LOS) variables (*time, cost, distance*). μ_{jn} is the alternative-specific error component that captures the individual (Train 2009) correlation with zero mean and standard deviation σ_μ ; ε_{jn} is the GEV (Generalized Extreme Value

distribution) error term, identically, and independently distributed. The values of the alternatives are (j values): car driver, car passenger, train, BTM, cycling, and walking.

The socioeconomic parameters were tested as both generic and alternative-specific and the most statistically significant specification was then selected. The subscripts refer to person or individual (n), trip (t), and alternatives (j). The superscripts of the (beta) parameters represent the variables' vectors. The summation elements represent the vector sizes.

Simulation is usually applied to estimate the mixed logit model since it includes multiple time-situations per respondent. Given that the values that describe the population parameter of the individual parameters as R values of μ_{jn}^r are drawn from its distribution and the probability is calculated conditional on each realisation, the simulated probability is the average of the conditional probabilities over R draws:

$$SP_n = \frac{1}{R} \sum_{r=1, \dots, R} L_{ni}(\omega^r) \quad SP_{jnt} = \frac{1}{R} \sum_{r=1, \dots, R} L_{ni}(\mu^r) \quad (2)$$

Both inertia and choice models are estimated simultaneously. The simulated log-likelihood (SLL) function can then be constructed as $SLL(\mu_{jn}) = \sum_{n,j} \ln(SP_{jnt})$ and the estimated parameters are those that maximize the SLL. SLL decreases as the number of repetitions increases (Train 2000). The number of draws to use is a trade-off between computational time and accuracy (Hensher and Greene 2002).

Section 3.3 explains the incorporation of inertia effects for M3. The models were estimated with the BIOGEME extended package (Bierlaire and Fétiarison 2009).

Availability of alternatives

In the model structure, alternatives were included as available depending on specific constraints. For example, only respondents who declared to have a car and driver's license received the alternative "car driver" as an available alternative. For PT (Public Transport) only when a possible PT route was existing for the reported Origin–Destination trip, the alternative PT was available.

Modeling of inertia effects

The following expression describes an indicator of inertia (I_{jn}^w), assuming that an individual n evaluates the alternative j in the current situation w , considering the utility that the alternatives j had in the previous situation $w-1$ (V_{jn}^{w-1}), and the individual compares this utility with the utility of the alternative r that was chosen in the previous choice situation² $t-1$ (V_{rn}^{w-1}). Therefore, the inertia in the first wave is zero, which means that inertia is accounted for from the second wave onwards. The expression indicates that inertia in the current choice situation w (wave) can vary with socioeconomic characteristics. α_{ij}^w is the associated parameter to be estimated.

$$I_{jn}^w = \left(\alpha_{ij}^w \right) \left(V_{rn}^{w-1} - V_{jn}^{w-1} \right) \quad (3)$$

² w is the wave; t is representing the decision situations within a wave. In the inertia model, we refer to the previous wave; t is used in M2 to represent that a respondent faces multiple decision situations over time.

I_{jn}^w is the *inertia* indicator. Inertia can be positive (keeping the habit) or negative (high disposition to change). The inertia effect is calculated for each pair of waves, and the coefficient is estimated simultaneously with the choice model, this coefficient is shared over pairs of waves. We introduce inertia as alternative specific, since the effects can vary per choice (e.g. transport mode). As discussed in Yanez et al. (2010), the attributes of the inertia effects, which are measured as the difference in utilities, are continuous and vary among options and individuals. Therefore, there is no identification issue.

Therefore, M3 was developed by adding the inertia term (I_{jn}^w) to the DCM (Eq. 1). The utility of alternatives in $w-1$ is written as:

$$U_{jn}^{t,w-1} = ASC_j^{w-1} + \sum_l \beta^s SE_n + \sum_r \beta^z Z_n + \sum_m \beta^M M_n \\ + \sum_d^{LE} \beta^{LE} LE + \sum_h \beta_j^{LOS} LOS_{jn}^t + \mu_{jn} + \varepsilon_{jn}^{w-1}$$

And the utility of the subsequent waves is written as:

$$U_{jn}^{t,w} = ASC_j^w + \sum_l \beta^s SE_n + \sum_r \beta^z Z_n + \sum_m \beta^M M_n \\ + \sum_d^{LE} \beta^{LE} LE + \sum_h \beta_j^{LOS} LOS_{jn}^t - I_{jn}^w + \mu_{jn} + \varepsilon_{jn}^w \quad (4)$$

Here, SE_n is a vector of socioeconomic (individual, household) characteristics and survey elements (year, month, etc.), Z_n represents a vector of neighbourhood (e.g. accessibility) characteristics, M_n represents the mode preferences, LE_n indicates the life events and LOS represents travel-related attributes with vector size h , while μ_{jn} is the alternative-specific error component that captures the individual and household correlation with zero mean and standard deviation σ_μ . ε_{jn} is the GEV error term, identically and independently distributed.

The (logit) probability is then estimated as a joint probability product of the probabilities between waves. It represents the probability of a sequence of (wave) modal choices evaluated at the parameters. An integral is computed over the distribution of respondents for each time (t) and wave (w).

$$P_{ni}^w = \int_{\omega} \prod_{wt} L_{ni}(\omega_{ni}) f(\omega_{ni}) d\omega \quad (5)$$

Since with non-zero error components, the utility is correlated over alternatives (Train 2009), the estimation involves a covariance matrix of the random portions. The estimation is a function of the conditional choice probabilities, as many waves (w) are involved in the sample. It means that, when the four waves are in the sample, we have four sets of equations of mode choice and the joint probability is the product of the conditional probabilities. The impact of panel effects on travel cost sensitiveness is estimated by comparing estimates of a multinomial logit mode choice model with a mixed logit model with error components.

Elasticities

Via the estimation of cost parameter as the explanatory variable of mode choice, the elasticities of cost can be calculated. Estimation of cross-elasticities is possible via the calculation of elasticities between car cost and other transport modes, and vice versa. The direct elasticity shows the change in probabilities when an attribute of the alternative changes in the wave w . Therefore, being P_{ni}^w the probability of the alternative i the (point) elasticity is calculated as the derivative of the probability of i concerning the x variable (e.g. cost), and can be interpreted as the percentage change in the dependent variable for a given percentage change in the relevant independent variable (Ortúzar and Willumsen, 2011), expressed as follows:

$$E_{ni}^w = \frac{\partial P_{ni}^w}{\partial x_i} \cdot \frac{x_i}{P_{ni}^w} \quad (6)$$

Elasticities can take on both positive and negative values. Negative elasticities indicate a decrease in the share given an increase in the analysed variable (e.g., cost or time). Similarly, a positive elasticity means an increase in the market share given an increase in e.g. cost or time. The elasticities were calculated with Biogeme software package according to Bierlaire (2017). The elasticity was calculated per observation (trip) and the aggregate direct point elasticity is calculated concerning the value x . The result is an average of the disaggregated elasticities.

Model results

Inertia effects

Table 3 shows the comparison of model results for M1, M2, and M3. As can be observed, M3 was estimated for both pairs and three waves to show the inertia effects in a different time, as two and three waves of the survey, while M1 and M2 were estimated for the full sample of four waves. For Models with three waves samples, inertia parameter is a common term between waves two and three. We can observe that car users and cyclists show inert travel patterns. Table 3 shows the inertia effects for two and three waves simultaneously. The estimated I_{jn} parameters indicate that respondents' behaviour displayed a significant contribution to the utility (habit) from the behaviour in the previous wave ($w - 1$). As we can observe, inertia effects vary per wave, and (almost) all inertia parameters are statistically significant. This finding is remarkable from this study since other studies of inertia effects that only considered two waves. We can also observe that signs of inertia effects remain significant across the estimations. For example, for car users, the coefficient is (also) positive, and in 2013–2014 the smallest of the inertia parameters.

We can also observe that I_{car} is always smaller than the inertia coefficient for walking, and in 2013–2014 (2 waves) smaller than the public transport inertia parameter, showing stronger habits among car users than both public transport users and pedestrians. The contribution to the utility function is negative towards the choice in the second wave since

the inertia parameter is specified with a negative sign in the equation of wave $t+2$. For example, the person chose a car in the first wave and BTM in the second wave. The coefficient of inertia car is negative towards the utility of the BTM, decreasing the probability of choosing BTM in the second wave. This finding is consistent with González et al. (2017) who found a negative sign in the inertia parameter for car use since the sign of inertia in the utility function is negative. Car users have a significant disposition to maintain the usual choice (habit). The strongest disposition to change is revealed for the pedestrians, which means that pedestrians show a lower tendency to maintain their previous choice (habit). Unfortunately, the inertia parameter for cycling was unstable and unidentifiable when the model was estimated with a high number of draws.

Additionally, we can observe that most socioeconomic characteristics (gender, age, driving license, education level, and income level) and life event parameters are consistent in sign, whereas magnitude sometimes differs between the models, for example in the parameters for the life event variables (having a new job, having a child, starting work). We can also observe that LOS parameters differ in the estimations of M3, which can be attributed to the inclusion of the inertia parameter and the use of a sub-sample. All costs parameters are negative, as expected. Furthermore, cost parameters are substantially significant for model M3- with 4 waves, which indicates that individuals are still very sensitive to LOS over time. The standard deviations of the error components are significant in M2 and M3. Also, it is less significant in the M3s, indicating that inertia covers part of the individual heterogeneity captured by the error components in M2. Furthermore, some parameters and standard deviations of error components (intrapersonal effects) are less significant in the estimation of four waves of data (M2), indicating a decreased effect of the socioeconomic characteristic when the inertia effects are considered.

Regarding the socioeconomic characteristics, we can observe that adding several socioeconomic characteristics significantly improved the model specification. For example, age, work trip purpose, and driving license. The negative sign for the estimated parameter age (as a continuous variable), indicates that older people are less willing to use public transport (both BTM and train) than any other mode (car, bicycle or walk). Concerning work trips, it can be seen from the estimated parameter (purpose–work) added in the utility function of car driver and car passenger, that public transport is a significantly popular mode for work trips. Having a driving license was only added to the utility function of car-passenger. It was not included in the utility function of car-driver for identification purposes, because all people who drive a car have a driving license.

With regards to the neighbourhood accessibility variables, we can observe from the table that both public transport ($\beta_{\text{accessibility}_{OV}}$) and parking ($\beta_{\text{accessibility}_{PARK}}$) accessibility are positively significant for PT and car use, respectively. However, this sign is not consistent across waves. Also, the results show that life event variables are significant when inertia effects are considered (M3), while these variables are insignificant when the inertia effects are excluded (M1 and M2). It means that allowing the utility of the previous choice to affect the utility of the present choice modifies the effect of important changes in life (e.g. starting a new job, childbirth). It also shows that the panel model (M2) can better capture the effects of life events than the standard logit model (M1).

Furthermore, as we can observe, life-events (e.g. starting to work and having a new job) were significant in the presence of inertia effects (M3) but insignificant for M1 and M2. Life events have strong influences on transition probabilities between revealed behavioural patterns over time (Kroesen 2014). It reasonably means that life events might show high significance when patterns over time are explicitly analysed, as in the inertia model (M3). By contrast, life event parameters were not significant in M1 and M2, and therefore not included in the model. The results show that driving more is associated with getting a new job. Additionally, it shows that the effect of life events is more noticeable when inertia effects are included in the model. The result is consistent with Dutch panel studies that show that driving is very steady in the Dutch population (Yang and Timmermans 2015). Our finding adds to these studies by showing the interaction between life events and inertia effects.

Results from M2 show that intrapersonal effects are relevant for modelling mode choice. Table 3 shows that intrapersonal effects (σ_{μ}) parameters are statistically significant ($t\text{-test} > 1.96$). We can observe that the Mixed Logit model with the intrapersonal effect performs better than the Model 1 without intrapersonal effects. Intrapersonal effects are labelled as σ_{BIKE} , σ_{BTM} , $\sigma_{\text{(CAR_D)}}$, $\sigma_{\text{(CAR_P)}}$, and σ_{TRAIN} . All intrapersonal parameters (σ 's) are significant. The goodness of fit shows that M2 is a better model than M1, as expected. The addition of intrapersonal effects brings more robust results. Regarding the goodness of fit measures, we use the BIC and AIC criterion to compare the models, since these are estimated with different samples. The BIC and AIC penalize the number of parameters and are independent of the prior (e.g. prior value of LL, as the rho-squared). Lower values of BIC and AIC means a better model. Comparing the models with the same sample size M1 and M2, the BIC and AIC criterion show that M2 is the most robust model, which is reasonable because it performs the most realistic estimation of behaviour by considering intrapersonal effects. Also, due to different model specification certain differences can be observed between parameter values and t-test. M1 is a standard MNL, M2 is a MNL with panel effects and M3 is MNL with panel effects and inertia effects.

Intrapersonal variation (panel effects)

Table 3 Model results for M1, M2 and M3

Name	M1–All waves		M2–All waves		M3–2013 2014		M3–3 waves 2014 2015 2016	
	Value	t-test	Value	t-test	Value	t-test	Value	t-test
$ACS_{Cur_D}^{-w1}$	1.280	12.380	− 0.839	− 1.88	0.28	3.92	0.349	5.50
$ACS_{Cur_D}^{-w2}$							− 1.42	− 21.25
$ACS_{Cur_D}^{-w3}$							− 1.5	− 19.58
$ACS_{Cur_P}^{-w1}$	− 0.669	− 24.190	− 4.45	− 33.9	− 5.20	− 24.73	− 2.51	− 22.89
$ACS_{Cur_P}^{-w2}$							− 3.88	− 31.10
$ACS_{Cur_P}^{-w3}$							− 4	− 27.50
ACS_{Train}^{-w1}	0.226	2.550	− 27.1	− 22.9	− 4.19	− 13.91	− 3.8	− 5.82
ACS_{Train}^{-w2}							− 2.83	− 6.11
ACS_{Train}^{-w3}							− 3.65	− 6.65
ACS_{BTM}^{-w1}	0.164	1.730	− 8.23	− 14.26	− 4.56	− 20.04	− 7.03	− 13.10
ACS_{BTM}^{-w2}							− 3.13	− 6.14
ACS_{BTM}^{-w3}							− 2.9	− 4.95
ACS_{BIKE}^{-w1}	0.891	72.420	0.164	3.17	− 3.82	− 29.14	− 4.99	− 15.22
ACS_{BIKE}^{-w2}							− 9.37	− 17.94
ACS_{BIKE}^{-w3}							− 5.27	− 11.71
Socioeconomic characteristics and life events								
car passenger	− 0.355	− 23.480	− 1.12	− 16.32	− 0.06	− 3.93	− 0.067	− 3.760
$\beta_{female_{driver}}$	0.790	31.230	2.09	25.73	2.27	22.53	1.240	18.960
$\beta_{driver-license}$ (BTM)	0.088	3.520	0.68	7.95	2.15	21.62	1.610	27.890
$\beta_{medEducation}$ (Car driver)	0.337	6.750	1.51	6.87	0.08	2.27	0.115	4.510
$\beta_{educationHigh}$ (Car driver)	0.095	1.750	0.83	3.52	0.04	1.03	0.082	2.580

Table 3 (continued)

Name	M1–All waves		M2–All waves		M3–2013 2014		M3–3 waves 2014 2015 2016	
	Value	t-test	Value	t-test	Value	t-test	Value	t-test
BTM)	– 0.240	– 3.500	0.05	0.22	0.40	4.16	– 0.237	– 1.030
-work	0.446	7.130	1.46	8.32	0.42	4.53	0.440	2.170
-work	0.965	15.940	4.00	15.17	1.44	13.85	1.490	6.110
-work	0.261	14.160	0.67	13.10	0.56	10.44	0.602	8.230
New job/car	0.249	11.260	0.56	7.64	0.43	5.73	0.167	2.660
Started job/BTM, train	0.170	2.130	– 0.08	– 0.20	– 0.30	– 1.61	0.204	0.620
childbirth / bike	0.356	21.200	1.74	25.14	– 1.92	– 8.65	– 1.770	– 6.050
<i>Inertia and LOS</i>								
–								
					1.79	9.23	0.32	30.08
					1.23	12.15	4.92	19.45
					13.40	18.78	16.30	10.47
					0.40	12.58	0.34	3.34
	0.166	9.000	0.51	7.22	0.01	1.92	0.02	3.39
$\beta_{accessibility_{ov}}$	0.019	2.940	0.06	2.23				
$\beta_{accessibility_{park}}$	– 31.100	– 43.580	– 31.30	– 39.76	– 30.20	– 22.28	– 28.70	– 11.63
$\beta_{BTM_{cost}}$	– 6.270	– 31.210	– 10.70	– 29.12	– 1.17	– 9.37	– 1.62	– 4.04
- ratio cost/time	– 0.779	– 1.620	– 2.61	– 4.32	– 169.00	– 14.64	46.90	3.52
- ratio cost/time	– 24.200	– 49.950	– 25.10	– 46.27	– 24.10	– 23.21	– 24.80	– 10.82
<i>Intrapersonal effects</i>								
–w1			– 4.83	– 53	– 7.73	– 40.86	– 8.51	– 20.42
–w2/w3							– 16.10	– 21.36
–w1			– 4.54	– 49.55	0.00	0.05	– 0.01	– 1.07
–w2/w3							0.07	0.73
–w1			3.64	36.74	4.08	30.68	2.51	39.49
–w2/w3							0.21	1.79

Table 3 (continued)

Name	M1–All waves		M2–All waves		M3–2013 2014		M3–3 waves 2014 2015 2016	
	Value	t-test	Value	t-test	Value	t-test	Value	t-test
–w1			16.4	27.94	4.55	25.32	6.12	22.95
–w2/w3							– 0.10	– 0.78
–w1			– 7.65	– 21.69	– 4.30	– 28.11	– 8.25	– 18.97
–w2/w3							– 0.11	– 0.97
Goodness of fit								
Number of draws	250	250	250	150 ^a				
Number of estimated parameters	32	37	32	47				
Number of respondents	4256	4256	3649	2169				
Sample size	91,419	91,419	56,645	73,252				
Excluded observations	0	0	34,774	18,167				
Final LL	– 110,489	– 9931	– 155,480	– 327,346				
Bayesian information criterion BIC ^b	221,264	182,407	311,311	655,219				
Akaike information criterion AIC ^c	221,028	182,125	311,024	654,787				

^aSince the specification process implied iterations between the different models, the number of draws was optimized between 150 and 250 to obtain a reasonable computation time and robustness of the parameters. It was tested that 150 and 250 accomplished the same results.

^bBIC = $\ln(n)k - 2\ln(L)$; n – number of observations or sample size.

^cAIC = $2k - 2\ln(L)$ Let k be the number of estimated parameters in the model. L is the maximum value of the likelihood function for the model.

Model implementation: point elasticities

This section presents the direct and cross elasticities of cost. Also, we calculated direct and cross-elasticities with and without the inertia effects. Table 4 shows the point elasticities for car, BTM, and train costs. If car costs were to increase by 1%, the probabilities of the alternative mode of driving car would drop by 0.18% in the case of M1 (without intrapersonal effects) and by 0.17% in the case of M2 (with intrapersonal effects). Table 4 also shows that, in relative terms, the train cost scenario has a significant impact in comparison with the car cost scenario, consistent with previous findings (Paulley et al. 2006). Table 4 also shows the arc elasticities for a change of 1% in BTM costs. We can observe that the BTM market share would drop by 2–4%, whereas the train would attract more passengers (cross-elasticity of 0.06% for M2).³ Comparing the three scenarios of travel cost changes, we can conclude that the car market share is the least elastic demand, while public transport is more elastic. This result is consistent with the work of González et al. (2017), who found that car users give less importance to variations in travel cost and travel time than users of public transport.

When comparing the point elasticities among the different models (M1, M2, and M3), we can observe that elasticities are smaller with the inertia model (M3). Considering inertia effects (M3) yields smaller car-related (direct and cross-) elasticities of travel costs than the intrapersonal data models (M2). By contrast, both direct and cross-elasticities of BTM costs are larger in M3 than in M1 and M2. This result is also in line with the previous finding that models with inertia yield smaller car-related direct elasticities and increasing asymmetric effects between car use and public transport use (González et al. 2017). As can be seen, the inertia model produced smaller elasticities for travel by car; ignoring inertia effects might lead to overestimations of demand for car travel.

This is in line with literature on fuel price elasticities showing stronger effects in the long term (e.g. one year after the change) than in the short term (Goodwin et al. 2004). A comparison with literature shows slightly different values, but proportional differences of the car elasticities for M1, M2, and M3. Particularly, the values of car direct elasticities are smaller than other studies. For example, González et al. (2017) found elasticities of car costs of -0.63 and -0.34 for the models without temporal effects and inertia effects, respectively. Also, Dahl (2012) found, among 240 studies, that the median price elasticities are -0.34 and -0.16 for gasoline and diesel, respectively. It means that Dutch car drivers are less willing to change car habits than other studies in the literature. However, differences can also be related to: (1) the measurement of price changes in the existing studies, i.e. historical database, versus the 1% measured in our elasticities formulation; (2) the construction of non-chosen alternatives since we used longitudinal RP data.

Car cost cross-elasticities on BTM and train are larger than the public transport (cost) cross elasticities for car cost, consistent with González et al. (2017). And, the magnitudes of BTM and train elasticities are larger in M1 and M2, compared to other models without temporal effects (e.g. -2.77 in González et al. 2017), while M3 shows similar values. This effect can be derived from the choice set. For example, our choice set includes BTM as a combination Bus-Tram-Metro, while other experiments included bus as a separate alternative from the train. Furthermore, our model shows stronger differences between models

³ When the cost of travel by BTM increases, a certain share of people would prefer to travel by train. In the Dutch context, it is common to find BTM and train modes sharing stations, and tram-train sharing a few stops along a route.

Table 4 Cross and direct (point) elasticities (second wave)

	Cost elasticities				Relative changes between models and waves			
	Car driver	BTM	Train	Bicycle	Car driver	BTM	Train	Bicycle
					<i>Relative changes between models</i>			
M1—Car	− 0.18	0.02	0.02	0.01	6%	654%	680%	1420%
M2—Car	− 0.17	0.16	0.16	0.08	84%	− 87%	− 84%	− 93%
M3—Car 2013–2014	− 0.03	0.02	0.02	0.01	<i>Relative changes between waves</i>			
M1—BTM	0.02	− 4.35	0.02	0.02	21%	− 4%	134%	− 44%
M2—BTM	0.02	− 4.18	0.06	0.01	− 20%	− 18%	− 126%	− 179%
M3—BTM 2013–2014	0.02	− 3.43	0	− 0.01	<i>Relative changes between waves</i>			
M3—BTM 2014–2015	0.03	− 2.31	0.02	0.01	− 45%	− 33%	− 257%	− 211%
M3—BTM 2015–2016	0.02	− 3.01	0	0	24%	30%	− 110%	− 79%
					<i>Relative changes between models</i>			
M1—Train	0.02	0.02	− 5.73	0.02	30%	134%	3%	− 42%
M2—Train	0.02	0.06	− 5.9	0.01	− 52%	− 114%	− 16%	− 119%
M3—Train 2013–2014	0.02	− 0.01	− 4.96	0	<i>Relative changes between waves</i>			
M3—Train 2014–2015	0.03	0.02	− 4.21	0.01	− 29%	− 297%	− 15%	− 453%
M3—Train 2015–2016	0.01	0.02	− 7.63	0	53%	1%	81%	− 56%

When the sample included more than two waves, the inertia term was measured in wave two and subsequently

M1, M2, and M3, probably due to the differences in the number of waves included in each model. Other studies used only 2 waves of data as RP and SP, instead of explicitly collected panel data.⁴

When computing the average car cost cross-elasticities of train, BTM, and bicycle for M1, M2, and M3, the results (+0.06) are consistent with the findings by Litman (2017) who summarized that the modal shift to transit when fuel price increases around +0.07, see for example Luk and Hepburn (1993). It is important to note that, when temporal effects are considered (see for example M3 for 2013–2014), this shift sums to 0.05.⁵ It is important to note that the comparison of elasticities is not straightforward. Dahl (2012) found 220 unique equations among 240 studies of elasticities.

Table 4 also shows the relative changes between the elasticities calculated from Models 1, 2, and 3, with intrapersonal effects and inertia effects, respectively, and the elasticities between waves of M3. We can observe that the most drastic differences occur with the elasticities of car cost between waves of M3. Similarly, the most substantial differences between models occur for the alternative bicycle M1 versus M2 with the car cost elasticities, which means that car cost elasticities are very susceptible to both temporal (habit/

⁴ The parameter of cost belongs to a ratio between cost and time to be able to estimate negative coefficients of cost for most of the alternatives across the waves. Unfortunately, car cost/time coefficients were still positive for waves 2014–2015 and 2015–2016. Therefore, the models for three and four waves are included. Additional estimations, available upon request, show similar results for a sample of stayers only, and fixed travel time coefficients.

⁵ The shift is represented by the sum of the elasticities of the specific modes.

inertia) and intrapersonal (individual correlation) effects. And these effects are stronger than public transport elasticities.

Conclusions and discussion

This paper examines the influence of intrapersonal effects and inertia in travel behaviour and the impact on travel cost elasticities. The analysis is based on four waves of the Mobility Panel for the Netherlands, using a sample of around 90,000 trips. We estimated three discrete choice model types: (1) a standard multinomial logit, (b) a standard mixed logit model with error components that capture within wave day-to-day variability in mode choice (panel effects) given by multiple observations of the same individual, (c) a hybrid mixed logit model capturing inertia in mode choice between waves (years). The effect of inertia on travel cost elasticities is measured by estimating mixed logit mode choice models with and without inertia effects.

The first main conclusion is that both panel and inertia effects are significant and relevant in modelling mode choice. Inertia effects vary across transport modes and waves and impact travel cost elasticities. In relative terms, the largest (relative) differences due to individual and temporal correlation were found for car users and cyclists. The models also show that both travel time and travel costs are statistically significant for mode choice, and personal characteristics affect mode choice. Furthermore, life events such as moving to a new house and jobs are shown to have significant impacts on mode choice in the hybrid choice model which incorporated inertia effects. A second main conclusion is that car users are identified as inert travellers, whereas public transport users show a lower tendency to maintain their usual mode choice. Neglecting inertia effects can thus have consequences for the ex-ante assessment of transport pricing policies. Other panel studies also showed a significant degree of inertia of car use in response to fuel price changes (Yang and Timmermans 2014, 2015). Further, from the policy and planning perspective, the model implementation shows the impact of inertia on the elasticities of travel cost per transport mode. A biased calculation of elasticities of travel costs may have substantial impacts on policy implementation, for example on fuel price variations, toll road or road taxes.

Due to the use of the MPN and the implementation of the inertia effects, our paper aims to cover several methodological issues encountered when estimating elasticities of travel costs based on panel data. First, our paper shows on a closer scale, but also longer period than other papers. For example, Gonzalez et al. (2017) used RP/SP data collected two years apart. Our scale (1 to 4 years) the potential impacts of changes in both alternative attributes (e.g. cost, time) and socioeconomic variables (e.g. life-events, income). Therefore, we can identify in this short term which changes are the most influential on the choice process. Second, our study includes a full diary of trips undertaken over three days. Whereas other studies, e.g. The Santiago Panel used data from a pseudo diary (Yanez et al. 2010). Third, our sample is composed of all segments of the population. Other studies considered specific groups of the population, such as students (Gonzalez et al. 2017). Having a full representation of the population enables more transferable results. Therefore, the present paper aims to improve the elasticity calculation in the short-run (less than five years). It does not compare long versus short runs. Therefore, our approach is comparable with the estimation of elasticities in the short run.

The MPN survey is available every year, which would allow future extensions of this research. However, a drawback of the study is the computation time to estimate large sample sizes. Whereas, slower effects, e.g. specific life-events or impacts on preferences due to changes in land-use, are better reflected over longer periods, which implies more observations. Therefore, modelling “stayers only” samples over more waves is recommended. In the same line, a possible extension of this paper is to analyse the impact of travel cost changes on both mode and destination choice. This limits the impact of travel cost changes on vehicle miles travelled, and thus results are relatively small travel cost elasticities compared to the literature such as González et al. (2017). Future research on the impact of inertia and intrapersonal effects on transport elasticities could focus on adding more scenarios of increasing and decreasing travel costs. A further step might be to incorporate shock effects, e.g. price change shocks or major changes in the transport system. Also, the interaction between life events, car ownership, and mode choice decisions could be included in future studies. Also, when additional waves of the Mobility Panel for the Netherlands become available, it will be possible to study a long-time frame and capture more life events and inertia effects for a longer period.

Regarding other behavioral theories, our paper directs to policy implementations by calculating the elasticities and discussing the impact of the model structures on the travel demand. As accounted into the Reinforcement Learning (REL) Model (e.g. Yang et al (2017)), when there is no information about the alternatives, users receive feedback from the past. Transferred to the utility maximization theory implemented in our paper, this feedback is explicitly represented by the inertia parameter as the difference between utilities of alternatives previously chosen. However, other cognitive theories could also be explored in the behavioural framework of experience-based models (e.g. instance-based and cumulative prospect) to estimate elasticities of panel data.

Appendix A

Self-reported comparison

Table 5 below shows the average calculated versus the self-reported values. As we can observe, the calculated travel times were stronger in car trips, and weaker in public transport trips due to the consideration of access and egress travel times.

Table 5 Comparison of travel times reported versus calculated

	Car Driver	Train	BTM	Bicycle
Average difference (minutes) Travel Time Calculated – Travel Time Reported. Based on countable reported and calculated entries	– 0.55	– 2.78	– 1.91	– 2.95
Total blank records: OD pairs with a calculated, but without a reported travel time for that mode	7084	25,400	25,436	20,523
Total countable records: amount of OD pairs with both reported and calculated TT	19,351	1035	999	5912

Appendix B

Repetition of choices

To support the interpretation of results, The table below shows the repetition of choices per chosen mode. We can observe that car and bicycle and users are those repeating more often their choices, which is consistent with the results of the inertia parameters obtained.

See Table 6.

Table 6 Repetition of mode choice over different waves

Repetition of choice	Waves	Percentage
Repeated Car	2 waves	16.55
	3 waves	10.21
	4 waves	4.15
Repeated Car Passenger	2 waves	7.01
	3 waves	2.24
	4 waves	0.64
Repeated Train	2 waves	0.93
	3 waves	0.11
	4 waves	0.02
Repeated BTM	2 waves	1.01
	3 waves	0.20
	4 waves	0.06
Repeated Bicycle	2 waves	13.17
	3 waves	6.65
	4 waves	2.33
Repeated_walk	2 waves	7.12
	3 waves	2.79
	4 waves	0.78

Appendix C

See Table 7.

Table 7 Sample Characteristics

Variable	Car driver (%)	Car passenger (%)	Train (%)	BTM (%)	Bicycle (%)	Walking (%)	Total (%)
<i>Gender</i>							
Male	49.5	5.5	2.5	2.1	27.5	12.9	100.0
Female	36.1	12.9	2.1	2.2	32.4	14.3	100.0
Total	41.8	9.8	2.3	2.2	30.3	13.7	100.0
<i>Age</i>							
18–19	11.9	16.3	10.8	11.1	42.0	7.9	100.0
20–24	26.5	11.5	7.0	5.8	37.1	12.0	100.0
25–29	39.1	9.4	4.2	2.7	30.2	14.4	100.0
30–34	48.1	10.2	2.3	1.3	24.1	14.1	100.0
35–39	46.1	6.9	1.3	1.4	30.0	14.3	100.0
40–44	50.3	7.9	1.5	1.1	28.3	11.0	100.0
45–49	50.2	8.9	1.3	1.0	28.5	10.0	100.0
50–54	47.9	9.0	1.5	1.3	29.8	10.6	100.0
55–59	42.4	9.0	1.3	1.7	32.6	12.9	100.0
60–64	40.0	10.6	1.1	1.0	29.8	17.5	100.0
65–69	33.2	11.7	1.1	1.9	34.8	17.2	100.0
70–74	36.5	12.5	0.9	2.6	28.9	18.7	100.0
75–79	35.9	11.1	0.8	3.0	27.4	21.8	100.0
≥80	39.8	11.2	0.6	2.5	24.7	21.2	100.0
Total	41.8	9.8	2.3	2.2	30.3	13.7	100.0
<i>Education*</i>							
No education	14.3	8.2	10.2	34.7	20.4	12.2	100.0

Table 7 (continued)

Variable	Car driver (%)	Car passenger (%)	Train (%)	BTM (%)	Bicycle (%)	Walking (%)	Total (%)
Primary education	24.7	14.7	3.2	4.8	38.0	14.7	100.0
Secondary general education (age 13–17)	40.0	13.1	1.0	1.7	28.8	15.4	100.0
Preparatory (vocational) secondary education (age 13–17)	37.1	12.7	2.0	3.0	30.6	14.6	100.0
Tertiary (vocational) education (MBO) diploma	48.7	9.4	1.3	1.4	26.8	12.5	100.0
Senior general secondary and university preparatory education (HAVO and VWO)	32.7	10.8	4.5	3.7	36.0	12.3	100.0
Undergraduate education (Bachelor)	44.7	8.2	2.0	1.9	29.9	13.3	100.0
Postgraduate education (Master, PhD)	36.9	6.5	4.0	1.9	33.7	17.0	100.0
Unknown	45.9	21.3	0.0	6.6	23.0	3.3	100.0
Total	41.8	9.8	2.3	2.2	30.3	13.7	100.0
<i>Personal income</i>							
≤ €1,000	29.0	13.5	2.7	2.7	38.1	14.0	100.0
€1,001–1,500	42.2	10.9	1.4	1.5	29.1	14.8	100.0
€1,501–2,000	48.3	8.1	2.4	2.0	25.1	14.1	100.0
€2,001–2,500	49.6	6.4	2.2	1.4	27.9	12.5	100.0
€2,501–3,000	51.1	5.9	2.3	2.1	25.0	13.6	100.0
€3,001–3,500	53.6	4.9	1.7	1.6	25.2	13.0	100.0
Personal car ownership							
No	9.1	11.2	6.1	5.7	49.5	18.4	100.0
Yes	51.1	9.2	1.2	1.1	25.3	12.1	100.0
Total	41.8	9.8	2.3	2.2	30.3	13.7	100.0
<i>Driving licence</i>							
No	0	16.5	5.6	7.6	45.7	24.0	100.0
Yes	46.0	9.1	1.9	1.6	28.8	12.7	100.0
Total	41.7	9.8	2.3	2.2	30.3	13.7	100.0
Life events							

Table 7 (continued)

Variable	Car driver (%)	Car passenger (%)	Train (%)	BTM (%)	Bicycle (%)	Walking (%)	Total (%)
New Job (yes = 1)	40.9	9.3	4.2	3.2	29.9	12.4	100.0
Started job (yes = 1)	31.9	10.0	5.8	3.6	34.6	14.2	100.0
Child birth (yes = 1)	56.1	9.0	0.9	0.9	16.8	16.3	100.0
Urbanisation level	Car driver	Car passenger	Train	BTM	Bicycle	Walking	Total
Extremely urbanised (≥ 2500 addresses/km ²)	30.6	7.7	3.6	5.0	34.6	18.5	100.0
Strongly urbanised (1500 to 2500 addresses/km ²)	40.5	10.2	2.7	1.9	30.5	14.2	100.0
Moderately urbanised (1000 to 1500 addresses/km ²)	42.3	9.8	2.0	1.2	32.3	12.4	100.0
Hardly urbanised (500 to 1000 addresses/km ²)	48.5	10.4	1.0	1.3	27.2	11.7	100.0
Not urbanised (< 500 addresses/km ²)	53.8	11.3	1.4	1.2	22.5	9.7	100.0

Acknowledgements This work results from a research collaboration between the University of Twente and Goudappel Coffeng commissioned by Rijkswaterstaat WVL. The authors thank Paul van Beek from Goudappel Coffeng for coordinating the panel project and the Netherlands Institute for Transport Policy Analysis (KiM) for allowing access to the Mobility Panel for the Netherlands.

Authors' contribution Lissy La Paix: Wrote the whole paper except Sect. “Data source, enrichment, and description”, conducted the choice modeling analysis, estimated the models, designed the analytical framework; Abu Toasin Oakil: Wrote Sect. “Data source, enrichment, and description” of the paper, assisted in the estimation of preliminary models, prepared the database for modeling, added enrichment variables to the dataset of the non-chosen alternatives. Frank Hofman: Reviewed the paper and made comments, edited text. Karst Geurs: Reviewed the paper, made comments, contributed with writing sections, edited text.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

- Bierlaire, M., Fétiarison, M., 2009. Estimation of discrete choice models: extending BIOGEME, 9th Swiss Transport Research Conference, Ascona, Switzerland.
- Bierlaire, M (2017) Calculating indicators with Biogeme (**Chapter 3**) <https://infoscience.epfl.ch/record/229190/files/Bier17.pdf>
- Cantillo, V., de Dios, J., Ortúzar, H.C.W.L., Williams: Modeling discrete choices in the presence of inertia and serial correlation. *Transp. Sci.* **41**, 195–205 (2007)
- Cherchi, E. and Cirillo, C. (2010) On the day-to-day variability in modal choices: A mixed logit mode choice model on panel data. XVI Panamerican Conference. Lisbon, Portugal (on CD).
- Cherchi, E., Borjesson, M., Bierlaire, M., 2013. A hybrid mode choice model to account for the dynamic effect of inertia over time, International Choice Modelling Conference, Sydney, Australia.
- Cherchi, E., Cirillo, C., Ortúzar, J.D.D.: Modelling correlation patterns in mode choice models estimated on multiday travel data. *Transp. Res. Part A: Policy Pract* **96**, 146–153 (2017)
- Cherchi, E., Manca, F.: Accounting for inertia in modal choices: some new evidence using a RP/SP dataset. *Transp.* **38**, 679 (2011)
- Dahl, C.A.: Measuring global gasoline and diesel price and income elasticities. *Energy Policy* **41**, 2–13 (2012)
- Dargay, J., 2004. The Effect of Prices and Income on Car Travel in the UK, 10th World Conference on Transport Research, Istanbul.
- De Dios, J., Ortúzar, J.A., Madre, J.-L., Potier, F.: Continuous mobility surveys: the state of practice. *Transp. Rev.* **31**, 293–312 (2011)
- de Dios Ortúzar, J., Willumsen, L.G.: Modelling transport, 4th edn. Wiley, Chichester, UK (2011)
- de Haas, M.C., Scheepers, C.E., Harms, L.W.J., Kroesen, M.: Travel pattern transitions: Applying latent transition analysis within the mobility biographies framework. *Transp. Res. Part A: Policy Pract.* **107**, 140–151 (2018)
- González, R.M., Marrero, Á.S., Cherchi, E.: Testing for inertia effect when a new tram is implemented. *Transp. Res. Part A: Policy Pract.* **98**, 150–159 (2017)
- Ghader, S., Darzi, A., Zhang, L.: Modeling effects of travel time reliability on mode choice using cumulative prospect theory. *Transp. Res. Part C: Emerg.technol.* **108**, 245–254 (2019)
- Goodwin, P., Dargay, J., Hanly, M.: Elasticities of road traffic and fuel consumption with respect to price and income: A review. *Transp. Rev.* **24**, 275–292 (2004)
- Hensher, D.A., Greene, W.H.: The mixed logit model: the state of practice. University of Sydney, Sydney (2002)

- Hoogendoorn-Lanser, S., Schaap, N.T., OldeKalter, M.-J.: The Netherlands mobility panel: an innovative design approach for web-based longitudinal travel data collection. *Transp. Res. Procedia* **11**, 311–329 (2015)
- Jou, R.C., Chen, K.H.: An application of cumulative prospect theory to freeway drivers' route choice behaviours. *Transp. Res. Part A: Policy Pract.* **49**, 123–131 (2013)
- Kroesen, M.: Modeling the behavioral determinants of travel behavior: An application of latent transition analysis. *Transp. Res. Part A: Policy Pract.* **65**, 56–67 (2014)
- La Paix Puello, L., Olde-Kalter, M.-J., Geurs, K.T.: Measurement of non-random attrition effects on mobility rates using trip diaries data. *Transp. Res. Part A: Policy Pract.* **106**, 51–64 (2017)
- Litman, T., 2017. Understanding Transport Demands and Elasticities, In: Institute, V.T.P. (Ed.), VTPI.
- Luk, J., Hepburn, S., 1993. New Review of Australian Travel Demand Elasticities In: (Victoria), A.R.R.B. (Ed.).
- Oakil, A.T.M., Ettema, D., Arentze, T., Timmermans, H.: Bicycle Commuting in the Netherlands: an analysis of modal shift and its dependence on life cycle and mobility events. *Int. J. Sustain. Transp.* **10**(4), 376–384 (2016)
- Paulley, N., Balcombe, R., Mackett, R., Titheridge, H., Preston, J., Wardman, M., Shires, J., White, P.: The demand for public transport: The effects of fares, quality of service, income and car ownership. *Transp. Policy* **13**, 295–306 (2006)
- Peer, S., Knockaert, J., Koster, P., Verhoef, E.T.: Over-reporting vs. overreacting: Commuters' perceptions of travel times. *Transp. Res. Part A: Policy Pract.* **69**, 476–494 (2014)
- Tang, Y., Gao, S., Ben-Elia, E.: An exploratory study of instance-based learning for route choice with random travel times. *J. Choice Model.* **24**, 22–35 (2017)
- Thomas, T., La Paix Puello, L., Geurs, K.: Intrapersonal mode choice variation: Evidence from a four-week smartphone-based travel survey in the Netherlands. *J. Transp. Geogr.* **76**, 287–300 (2019)
- Train, K.: Halton sequences for mixed logit. University of California Berkeley, Department of Economics (2000)
- Train, K.: Discrete choice models with simulation, 2nd edn. Cambridge. University Press, New York (2009)
- van Exel, J.: Behavioural economic perspectives on inertia in travel decision making. Vrije Universiteit, Amsterdam, Faculteit Economische Wetenschappen en Bedrijfskunde (2011)
- Yanez, M., Cherchi, E., Ortuzar, J. d. D., Heydecker, B. G., 2009. Inertia and shock effects on mode choice panel data: implications of the Transantiago implementation, 12th International Conference on Travel Behaviour Research, Jaipur, India.
- Yáñez, M.F., Mansilla, P., de Dios Ortúzar, J.: The Santiago panel: measuring the effects of implementing transantiago. *Transp.* **37**, 125–149 (2010)
- Yang, C., Liu, B., Zhao, L., Xu, X.: An experimental study on cumulative prospect theory learning model of travelers' dynamic mode choice under uncertainty. *Int. J. Transp. Sci. Technol.* **6**(2), 143–158 (2017)
- Yang, D., Timmermans, H.: Effects of fuel price on individual dynamic travel decisions. *Transp. Res. Rec.* **2412**(1), 1–10 (2014)
- Yang, D., Timmermans, H.: Analysis of consumer response to fuel price fluctuations applying sample selection model to GPS panel data: Dynamics in individuals' car use. *Transp. Res. Part D: Transp. Environ.* **38**, 67–79 (2015)
- Yang, J., Jiang, G.: Development of an enhanced route choice model based on cumulative prospect theory. *Transp. Res. Part C: Emerg. Technol.* **47**, 168–178 (2014)

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Dr. Lissy La Paix is a Senior Transportation Engineer with 16 years of experience in Transport Planning and Mobility studies along with traffic modeling. Received a Doctorate by the Civil Engineering Faculty of Universidad Politécnica de Madrid. Expertise covers traffic analysis, discrete choice modelling, and travel behavior. Dr. La Paix is author of more than 30 scientific publication in international academic records of high impact. She was assistant professor at the University of Twente when this research was conducted.

Dr. Abu Toasin Oakil was a consultant at DAT.Mobility, the Netherlands when this study was conducted; currently, a senior research associate in KAPSARC's Transport and Urban Infrastructures program. He has worked as a scientific researcher at universities and public organizations, and as a consultant in the private sector. He holds a Ph.D. in transportation planning from Utrecht University, an M.Sc. in urban planning from the London School of Economics, and Bangladesh University of Engineering and Technology.

Dr. Frank Hofman works for Rijkswaterstaat, the Highway Department of the Dutch Ministry of Infrastructure and Water Management. His responsibility is to maintain and develop the traffic and transport models that are used within the Ministry and Rijkswaterstaat for ex ante policy evaluation and decisions with respect to road capacity.

Prof. Dr. Karst Geurs is appointed Full Professor of Transport Planning at the Centre for Transport Studies. His research focuses on interactions between land use and transport, accessibility modelling and evaluation and the dynamics in travel behaviour. He is chair of the Network on European Communications and Transport Activities Research (NECTAR), Editor-in-Chief of the European Transport Research Review (ETRR) and member of the Editorial Advisory Board of the Journal of Transport and Land Use (JTLU).