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Measurement of non-random attrition effects on mobility rates using trip diaries data

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ABSTRACT

This paper examines the influence of panel attrition on the intrapersonal dynamics in self-reported trip rates, using the data from the 2013, 2014 and 2015 waves of the Netherlands Mobility Panel, a large scale household panel. A hybrid choice model (HCM) was developed to simultaneously model the effect of socioeconomic, infrastructure and land use variables, life events and non-random attrition on trip rates, whereby the latent variable (LV) model is composed of panel attrition and survey completeness. The discrete choice model (DCM) includes four trip rate categories, including zero trips. The probability of each trip rate category was estimated for both the HCM and the DCM models; with and without the LV model. The first main conclusion from this paper is that the largest bias due to panel attrition occurs in the probability of reporting no trips per day, and 1–2 trips per day. Also, the HCM models show a correlation between the probability of reporting no trips per day and the tendency to drop out altogether. The second main conclusion is that the results show that the latent variables (attrition and completeness) are statistically significant in estimating mobility. Also, socioeconomic variables (gender, driving license, household type and size), mode preferences, spatial infrastructure and life events determine mobility rates and remain significant after adding attrition/completeness variables. Thirdly, the results proved that attrition effects significantly vary across waves.

1. Introduction

In most countries, the understanding of people's travel behaviour is based on cross-sectional travel surveys in which only one day is surveyed for each respondent; often also in 'representative' periods when traffic flows are maximal (see for an overview Ortúzar et al., 2011). This is not enough to gain a proper understanding of the dynamics in travel behaviour and the behavioural changes needed to reverse the worrying long-term trends of growing mobility, congestion, increasing oil consumption and greenhouse gas (GHG) emissions (Ortúzar et al., 2011). More specifically, cross-section travel surveys do not give any information to ascertain how choices will vary over time (i.e. policy response) if the system changes. Moreover, from the onset, the travel demand models that form the basis of transport policy making in many countries have been based upon these one-day cross-section surveys (Stopher and Zhang, 2011). The models implicitly assume that behaviour is adjusted to new circumstances instantaneously (i.e. behaviour is assumed to be in equilibrium, fully adjusting to the prevailing values of contributing factors) and travel patterns are highly repetitive in the short run. Both assumptions, however, do not hold. In the literature it is often reported that there are all sorts of factors that will not lead to travellers immediately adapting to new situations (e.g., see for overviews of literature Fujii, 2010; Meurs, 2007). Furthermore, there

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is a strong need for a larger data collection for survey data, which would also allow, for example, drawing a significant origin-destination matrix for traffic modelling (Castaigne et al., 2009).

Panel surveys trace the same individuals over time, and offer unique opportunities to both analyse and model the dynamics of travel behaviour. Such modelling can be performed at the individual level and enable identification of inter- and intrapersonal variation on travel behaviour. However, from the literature, it is well known that multi-day panel studies can introduce a bias. This means that respondents' abilities and intentions to keep accurate travel diaries, for a certain period of time, decreases. This bias is linked to the fact that trip diary data are collected from the same respondents at two or more points within the period (Kitamura and Bovy (1987), Ortúzar et al. (2011)). If respondents participate in a number of waves of a panel survey, fatigue can occur and introduce non-random variations in reported trips. Therefore, drop-outs are a common characteristic of all panel studies, occurring when certain sample units leave the panel in the second or subsequent waves. Annual and biannual transport panels typically lose between 20 and 40 percent of their participants per wave (Polak, 1999). For some panel experiments, attrition does not only occur *between* waves, but also *within* waves. Attrition *within* means that respondents do not complete part of the survey, within the same wave. On the other hand, attrition *between* means that respondents drop out from one wave to the next.

This paper aims to model intra- and interpersonal dynamics in trip rates while controlling for possible attrition biases in the panel data, using data from the Netherlands Mobility Panel (in Dutch: MobiliteitsPanel Nederland – MPN) (Hoogendoorn-Lanser et al., 2015). A hybrid choice model is developed to simultaneously model trip rates using socioeconomic and other travel behaviour variables and non-random attrition.

To the authors' knowledge, this is the first simultaneous model for non-random attrition and travel behaviour. Plus, we use data from the Netherlands Mobility Panel, currently the largest general purpose mobility panel in the world.

2. Literature review: travel behaviour and panel attrition

Understanding the dynamics in sociodemographic and attitudinal factors can well be called a crucial task in the analysis of mobility rates. There is evidence that at least 50% of the improvement in the overall model statistics can be due to the presence of repeated observations (Cherchi and Cirilo, 2008), and there is a strong element of habit or persistence in certain travel behaviour elements, e.g. household car ownership, from one year to the next (Nolan, 2010). Even so, Stopher and Zhang (2011) have shown that there is relatively little intrapersonal variation, which in their case referred to repetition of tours from one day to the next. It denotes the relevance of collecting high quality longitudinal data. The more variable behaviour is, the more flexible the supply needs should be.

A proper estimation of frequency of trips is the base for estimating travel behaviour. For example, frequency of trips is the best explanation for mode choice habits (Cherchi et al., 2013). Also, it has been found that several elements play an important role to estimate trip rates. For example, changes in lifestyle (Ma and Goulias, 1997; Meurs et al., 1989), changes in neighbourhood (Meurs and Haaijer, 2001), life-events, such as changing jobs or moving house (Clark et al., 2016), preferences for specific transport modes such as bicycle (Van Wee et al., 2002) and purpose-mode preferences (Schwanen and Mokhtarian, 2005), and use of the internet for shopping or work, within the household and/or individually (Farag et al., 2006; Francke and Visser, 2015; Kenyon, 2010). Therefore, a main advantage of panel data is to show individual day-to-day, but also year-to-year variation in terms of lifestyle and life events. However, a high risk point of panel data is *attrition effects*, this one and other relevant factors are elaborated in the following section.

2.1. How to measure non-random attrition and its correlation with trip rates?

Panel surveys are identified in the literature as an alternative to cross-section data collection (e.g., see Kitamura, 1990; Ortúzar et al., 2011; Zumkeller and Ottmann, 2009). Well-researched long duration panels are the 1971 Uppsala Household survey covering a 5-week time period (e.g., Hanson and Huff, 1988; Huff and Hanson, 1986), the six-week Mobi*drive* survey for the German cities of Karlsruhe and Halle, and related to this a survey in Thurgau (Switzerland). The Mobi*drive* panels have been used for example for analysis of the rhythms of daily life (Axhausen et al., 2002), and to measure variability in travel behaviour (Schlich and Axhausen, 2003).

Most panels reported in the literature are unrepeated short duration surveys due to the modest respondent burden and costs, compared to repeated and long duration panels. 'Unrepeated' means that multiple days travel data is collected but the survey is not repeated, or not with the same respondents. Furthermore, most repeated short duration panels in the literature were designed for specific purposes or projects. The Santiago panel, for example, was designed as a repeated (5 wave) short duration panel to evaluate the effects of the introduction of the Transantiago public transport system (Yáñez et al., 2010a). In Germany and the Netherlands general purpose mobility panels are used. The German Mobility Panel (MOP) has been conducted annually since 1994, using a seven-day trip diary (Zumkeller and Chlond, 2009), but it uses a rotating panel sample. The Mobility Panel for the Netherlands (MPN), a three-day trip diary, has been conducted annually since 2013 (Hoogendoorn-Lanser et al., 2015); and this is the largest ongoing panel in the world repeated with the same respondents.

However, there is a long-standing discussion over the reliability of longitudinal data in showing the real mobility patterns and *attrition* effects. Literature shows that *attrition* is almost always non-random; that is, the units that drop out are systematically different from the units that remain. For instance, research has shown that attrition can be related to households with lower incomes, educational levels, occupational status and less active mode use (see, for example, Kitamura and Bovy (1987) Pendyala et al. (1993),Hensher et al. (1992) and Brownstone and Chu (1997)). Lifestyles, too, might influence the *completeness* of the survey. For example, more mobile respondents can be more reluctant to complete the survey.

In its best-known incarnation, attrition has been simplified to a binary response (Kitamura and Bovy, 1987) while actually, several indicators of attrition can be named: temporary drop-out for an individual or household, permanent attrition between waves, and individual or household attrition within waves. These indicators might be correlated. For example, a member with a high probability of attrition *within* waves is less likely to stay in the next wave of the survey (drop out *between* waves). In addition, other authors found that the disposition of other household members' in a preceding panel wave strongly impacts the own participation behaviour (Lipss, 2006). The German socioeconomic panel SOEP (Kroh, 2013) already considered *temporary* drop-outs, both at the individual and the household level, in their analysis of refusal to participate in the survey. Still, a joint multidimensional representation of attrition is infrequently found.

Kitamura and Bovy (1987) analysed attrition *between* waves, and found a notable association between attrition and underreporting. The appearance of *between*-wave underreporting means that members could face fatigue, forget certain trips, report immobility or not complete their travel diaries. As a means to avoid this fatigue, some authors recommend samples of only 1 week for panel studies (short panel) (Yáñez et al., 2010a). While other authors manifested that fatigue is not an issue in long-duration diaries, which can also bring positive effects, i.e. learning (Axhausen et al., 2007). Different methodologies have been used to measure underreporting. See, for example, Kitamura and Bovy (1987), Meurs et al. (1989), Yang et al. (2010). However, the explicit connection between mobility rates (reported trips) and *attrition* has not been developed yet.

Furthermore, experienced members (*stayers*) may keep their diaries differently than new members (*refreshment sample*) (Meurs et al., 1989). For example, stayers and gatekeepers[1] who are experienced members might take more care to ensure *completeness* of the travel diary. Also, Meurs (2007) recommends devising models that include a term for drop-out (or *stayer*). Still, a problem arises when differences in mobility between stayers and drop-outs remain. To solve this, some authors have analysed the patterns of a *refreshment* sample, and predicted non-random attrition. A refreshment sample distinguishes the time-variant effects; s/he belong to the same wave of other stayers/drop-outs. If the *refreshment* batch also travel less than stayers, then this confirms that experienced respondents are more mobile. For example, Ridder (1992) developed an *attrition* model, with regression of attrition and explanatory variables being included in the survey (non-random attrition). They found significant individual and household correlations. They also found that mobile families were less likely to leave the panel. Nevertheless, these authors assumed that attrition effects were the differences between the parameters estimated for each wave. Therefore, an explicit (and numerical) connection between non-random attrition and trip rates – for example, the joint estimation of non-random attrition in the estimation of trip rates – is missing.

Similarly, Goulias et al. (2015) developed a longitudinal mixed Markov latent class analysis, in which each person belongs to a cluster. However, the attrition was taken to be the number of waves within which the model is estimated, without further explanations about the source of this attrition (education levels, income, household position, etc.), as being non-random attrition.

As shows from the literature, attrition has thus far been measured separately from travel behaviour. This precludes further interpretations regarding the interaction effects between individual mobility and *non-random attrition*, the latter being represented in this paper as the tendencies or propensity to accomplish certain tasks (e.g. report trips, stay in the panel, complete questionnaires).

In this paper, we contrast the socioeconomic characteristics, life events and individual characteristics with the propensity for attrition. We want to verify whether attrition masks the variation in reported trip rates. A hybrid choice model is developed to simultaneously estimate person trip rates and non-random attrition. We consider the correlation between individual and household using error components, following the approach taken by for example Hensher and Greene (2003) and Cherchi and Cirilo (2008).

3. Data and methods

3.1. Sample size and composition

The analyses in this paper are based on data from the first three waves of the MPN (2013, 2014, and 2015). The MPN was set up to study short-run and long-run dynamics in the travel behaviour of Dutch individuals and households, and to determine how changes in personal and household characteristics and other travel-related factors correlate with (changes in) travel behaviour. Hoogendoorn-Lanser et al. (2014) contains a description of the overall setup and design of the MPN and the philosophy behind the innovative design approach of the MPN's web-based diary.

Before the start, over 9000 households were approached to participate in the MPN (screening phase). Socioeconomic attributes related to the households and their members were collected for each participating household through household and individual questionnaires. Participants with a completed questionnaire were invited to keep a three-day online trip diary for three successive days (including weekend days). A trip is taken to mean a one-way course of travel from an origin to a destination with a single main purpose, which can comprise different stages linked to a change of mode. Individual questionnaires and trip diaries were only filled out by persons aged 12 and over.

Table 1 shows the number of participating households and individuals over the first three waves. In total, 5402 households and 11,322 individuals participated in one or more waves of the MPN; 3990 respondents did not complete the diaries. A total of 4355 respondents participated in multiple waves, of which 1779 participated in 3 waves.

Between the first and second wave, overall 18–28% of the participants drop out between questionnaires (household and individual), and 28% drop out between surveys (waves). Between the second and third wave, the attrition rate of households and participants with a travel diary is the same. The attrition rate of participants with an individual questionnaire is higher. This is mainly

[1] Gatekeepers are the contact persons within the household.

Table 1
Number of households and individuals participating in MPN 2013–2015 and attrition rate in 2013, 2014.

	Households	Individuals (questionnaire)[a]	Individuals (diary)
Starting sample			
2013	3571	6126	3996
2014	4685	9493	5551
2015	3125	5824	3919
Attrition rate			
2013	18%	22%	28%
2014	18%	28%	28%
Waves of participation			
2013	631	1346	1123
2013, 2014	793	1284	759
2013, 2015	58	230	335
2013, 2014, 2015	2089	3266	1779
2014	853	2643	1531
2014, 2015	950	2300	1482
2015	28	253	323
Multiple waves	3890	7080	4355
No diary			3990
Total	5402	11,322	11,322

[a] In the screening process, each person received an invitation to participate with 3 possible answers: (1) I am willing to participate, with complete response (questionnaire and diary), partial response (questionnaire or diary) or other; (2) I am not willing to participate; (3) no reaction. The difference between individuals questionnaire and diaries represents partial response. Some respondents completed the individuals questionnaire but did not continue to complete the individuals diary.

due to oversampling of younger people and multi-person households in the second wave, two groups with a higher probability of dropping out.

3.2. Definitions of attrition and completeness

For this analysis, we consider *attrition* (between and within) and *completeness*. Attrition *between* means that a respondent participated in wave *t* with a questionnaire and diary, but did not respond in the next wave. This means that *attrition between* waves is only possible for those participants who responded in full (questionnaire and diary) in at least one wave. The study does include *temporary drop-outs* as respondents who participated in 2 non-consecutive waves.

Attrition within means that the respondent did not complete all (three diaries) during the wave. This measurement is done at the individual level, as the number of diaries completed per individual-wave (*n_diary*). However, for identification purpose, we model *attrition within* at the household level as the difference between the total number of complete households based on questionnaires, and complete households based on diaries over the course of the 3 years.

Completeness means that full response of the survey (household questionnaire and individual diaries) was obtained for the respondent. Therefore, this measure refers to *completeness* within the household. A 'complete' household indicates that each household member completed the questionnaire (*completehh_quest)* or the questionnaire and diary (*completehh_diary*). In addition, we computed the sum of completed diaries and questionnaires (*completehh_quest_sum, completehh_diary_sum*) within the household across the 3 waves.

3.3. Descriptive statistics for trip rates

Table 2 shows the trip rates sorted by characteristics, at the individual level (age, gender, income, education), household level (presence of children, life events, etc.) and spatial level (perceived quality of infrastructure, city size). The columns in Table 2 show the average per group, where 'yes' means that the respondent belongs to the specific group, and 'no' means otherwise. The categories for the ordinal model were formulated based on this distribution. The average number of trips per day is around 3, from a total of 40,000 trips reported. The most relevant explanatory variables were selected based on the main differences that were identified from Table 2. These variables were included in the model specification. Examples are age, gender, household size, the life event of getting a new job, and the type of city. The next section contains further details about the model specification and results.

4. Analytical framework for the hybrid choice model (HCM)

The simultaneous trip frequency model incorporates both attrition/completeness and mobility equations. The analytical framework is based on the hybrid choice models developed by Ben-Akiva et al. (2002), and Walker and Ben-Akiva (2002). HCM incorporates latent variables into choice models. Fig. 1 shows the framework, in which the discrete choice (DCM) is shown on the left, and the latent variable model (LV) is shown on the right, with the corresponding measurement equations. As can be seen in Fig. 1, two types of equations are required: a *measurement equation (dashed arrows)* that links the unobservable *latent variable* to its

Table 2
Average number of trips per group of respondent.

Category	Variables	Average number of trips		T-test
Individual level		Yes	No	
Age	Teen (aged 17 or under)	2.54	2.97	–
	Adult (up to 64)	2.96	2.84	–
	Elderly (> 64)	3.01	2.92	*
Gender	Female	3.04	2.81	*
Employment	Unemployed	2.74	3.03	**
Head	Head of household	3.00	2.86	**
Education	None	2.61	2.94	**
	Basic	2.54	2.97	**
	Intermediate	2.72	2.99	–
	Higher (bachelor, master, doctor)	3.19	2.82	**
License	Possessing driving license	3.03	2.52	*
Life events	Start new job	2.89	2.94	–
	Going to work less often	3.09	2.93	–
	Going to work more often	3.09	2.93	–
	Change in work schedule	3.20	2.90	**
	Having a baby	2.91	2.94	–
E-shopping	Weekly	2.86	2.94	**
Preferences	Use preferred mode for work	3.03	2.83	**
Household level		***Yes***	***No***	
Household size	1 person in household	3.08	2.90	**
	2 persons in household	2.90	2.95	–
	> 2 persons in household	2.90	2.97	–
	Missing (n = 89)	2.93	2.93	–
Household gross income yearly	High (2 times > 65,000 per year)	3.06	2.95	–
	Income higher than minimum (> 5.000)	2.95	3.02	–
Children	Children < 6 years in household	3.29	2.89	–
	Children < 12 years in household	3.49	2.86	**
Household type	Single	3.08	2.90	**
	Couple without children	2.89	2.95	**
	Couple with children	2.92	2.95	**
	Single with children	2.87	2.94	**
Number of cars	No car in household	2.87	2.90	**
	1 car in household	2.98	2.95	**
	> 1 car in household	2.90	2.97	**
	Missing (n = 89)	2.93	2.93	**
Survey characteristics		***Yes***	***No***	
Travel day	Weekday trip diary belongs to working day (Monday to Friday)	3.14	2.43	**
	Saturday	2.91	2.94	**
	Sunday	1.94	3.10	**
Diary day: Trip diary belongs	First day	3.00	2.93	**
	Second day	2.93	2.94	**
	Third day	2.88	2.96	**
Stayer	3 years: 2013, 2014, 2015	3.12	2.81	**
	2 years Consecutive: 2013, 2014	2.95	2.93	**
	2 years Consecutive: 2014, 2015	2.90	2.95	**
	Non-consecutive: 2013, 2015	2.81	2.94	**
Year	2013	3.06	2.83	**
	2014	2.89	2.97	**
	2015	2.87	2.96	**
Month	September	3.21	2.90	**
Survey completed in:	October	2.91	2.95	*
	November	2.89	3.00	*
Spatial level		***Yes***	***No***	
Accessibility	Accessibility by car of home location is good	2.98	2.66	–
	Accessibility by PT of home location is good	2.95	2.91	*
	Accessibility by bicycle of home location is good	2.98	2.76	–
	Parking facilities at home location are good	2.95	2.90	–
Urbanity	Large city	2.81	2.97	*

– Not significant.
** Significant at 95% confidence level.
* Significant at 90%.

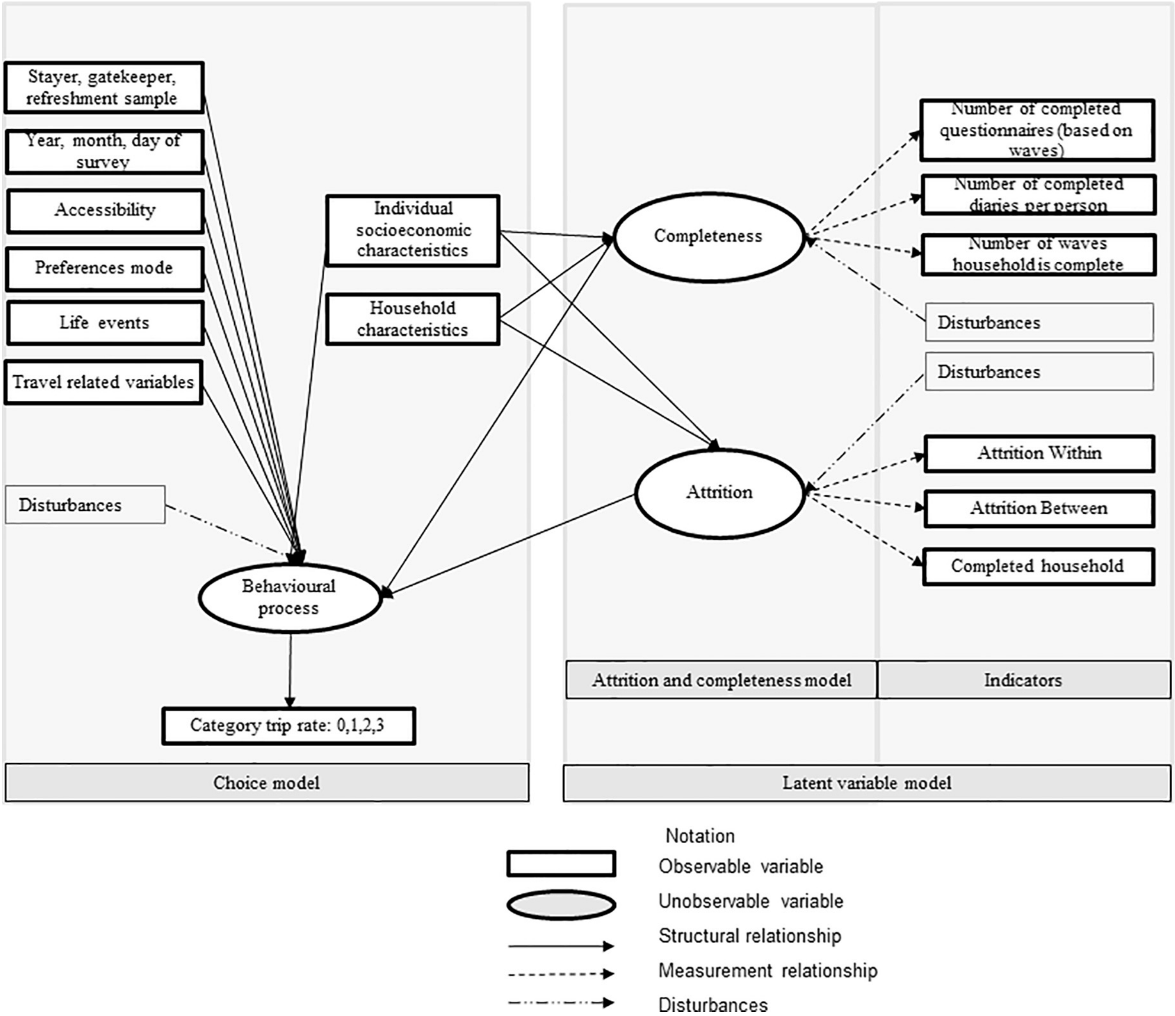

Fig. 1. Analytical framework for HCM model.

observable indicator, and a *structural equation (solid arrows)* that links the observable to the latent variables and models the behavioural process by which the latent variables are formed. Disturbances for both choice and latent variable models are represented by *dashed-dotted arrows*. Explanatory variables related to socioeconomic factors are added to both the DCM and LV model, whereas travel-related characteristics, life events, preferences and accessibility are added to the DCM model only. As can be observed, there are 2 LVs, the composition of which is explained in the coming sections.

4.1. The discrete choice model (DCM)

The discrete choice model was developed for trip rates and the total number of trips per day-respondent, based on 4 categories. These categories were created based on: (1) the number of respondents on each category (2) similar patterns are contained within the same category. For example, a respondent could report '1 trip' because s/he forgot the trip 'back home'. This effect on the model would be reduced by including 1 and 2 trips in the same category. Therefore, the J categories for the discrete choice model are:

- $J = 0$ if a person makes 0 trips per day
- $J = 1$ if a person makes 1–2 trips per day,
- $J = 2$ if a person makes 3–4 trips per day and
- $J = 3$ if a person makes more than 4 trips (Att_n) per day.

The choice model is based on the number of trips per person over the course of 3 days of diary data (trip rate). The choice model, in this case, U_{jn}, is the utility faced by individual n, undertaking j number of trips, from zero to 12 trips:

$$U_{jn} = ASC_j + \sum_i \beta_i^s S_{in} + \sum_r \beta_r^z Z_{nr} + \beta_j^{Att} Att_n + \varphi_{jn} + \varepsilon_{jn} \quad (1)$$

where the utility function is expressed as a function of a vector of socioeconomic characteristics (S_n), a vector of neighbourhood characteristics (Z_n), and the attrition propensity of each individual n. φ_n is the alternative-specific error component that captures the individual and household correlation with zero mean and standard deviation σ_φ. ε_{jn} is the GEV error term i.i.d. distributed.

4.2. The latent variable model (LV)

The latent variable is attrition or completeness propensity (*Att*). The structural equation for *Att* is specified as follows:

$$Att_n = \sum_k \lambda_k^s S_{kn} + \sum_m \lambda_m^z Z_{mn} + \omega_n \quad (2)$$

where Att_n represents Att_n^1 and Att_n^2 as the completeness and attrition propensity for individual n, respectively. S_n is a vector of SE characteristics with k elements, Z_n is a vector of survey attributes with m elements, λ^s and λ^z are two vectors of parameters associated with the SE and survey characteristics respectively, while ω_n is the error term, normally distributed with zero mean and standard deviation σ_ω.

The attrition model needs indicators, which are:

$$I_n = \alpha Att_n + \upsilon_n \quad (3)$$

where I_n is the indicator of the attrition (or completeness) propensity, for example: a dummy variable for drop-out, the number of completed questionnaires in the respondent household, the number of completed diaries in the respondent household, etc. is the associated parameter to be estimated and υ_n is the error term, normally distributed with zero mean and standard deviation σ_υ. Ordinal model structures were tested for the latent variable model, but given the ranges and low variability of the indicators (max. 4 points-scale), a continuous structure provided the best model fit, and it is used in this paper. See for example Bahamonde-Birke and Ortúzar (2017) for more discussion on the structure of latent variable indicators.

Since both the latent variable (Att_n) and its indicator of (I_n) are assumed to be normally and independently distributed, their distribution indicators (f_{Att} and f_I) are given respectively by:

$$f_{Att}(Att_n|\sigma_\omega) = \frac{1}{\sigma_\omega}\phi\left(\frac{Att_n - \sum_k \lambda_k^s S_{nk} + \sum_m \lambda_m^z Z_{mn}}{\sigma_\omega}\right) \quad (4)$$

$$f_I(I_n|Att_n;\alpha,\sigma_\upsilon) = \frac{1}{\sigma_\upsilon}\phi\left(\frac{I_n - \alpha Att_n}{\sigma_\upsilon}\right) \quad (5)$$

Hence the probability of individual n choosing the alternative j is the probability of choosing the alternative conditional on the observed and unobserved variables, given by:

$$P(j_n|S_n,Z_n,Att_n;\beta,\lambda;\sigma_\upsilon,\sigma_\omega,\sigma_\varphi) = Prob[U_{jn} \geqslant U_{in},j\ \forall \in C_n] \quad (6)$$

The measurement equation is defined, as in the typical discrete choice models, by an indicator (d_{jn}) that takes value one if the alternative chosen has the highest utility among all the alternatives available in the choice set of each individual. The maximum likelihood is obtained, as always, from maximizing the logarithm of the likelihood function ($\mathscr{L}$) over the unknown parameters:

$$\mathscr{L} = \sum_n \sum_{i \in C_n} d_{jn} \log P(j,I_n|S_n,Z_n,LOS_{nj};\beta,\lambda,\sigma_\varphi,\sigma_\upsilon,\sigma_\omega) \quad (7)$$

An integral is computed over the distribution of respondents for each period of time. Since with non-zero error components utility is correlated over alternatives (Train, 2003), the estimation involves a covariance matrix of the random portions. The models are estimated using the BIOGEME extended package (Bierlaire and Fetiarison, 2009).

4.2.1. Development of LV model – attrition and completeness

Through factorial analysis the indicators for both latent variables and, subsequently, its indicators were defined. Based on the factor scores, two LVs were identified as completeness (LV1) and attrition (LV2). Each LV is manifested by indicators:

- *Completeness*, as LV1, is manifested by three continuous indicators: the number of completed questionnaires per person (*n_quest*) from zero to three; number of waves the household is complete based on questionnaire (*completehh_quest_sum*) from zero to three; and the number of completed diaries (*n_diary*) per person, in a range from one to three.
- *Attrition*, as LV2, is manifested by three indicators, two of them are dummy variables: attrition within, attrition between and 'complete household based on diary'. *Attrition within* is represented as difference in household level between questionnaires and diaries completed. It varies from zero to three, being zero the most completed household, therefore the lowest '*attrition within*'. *Attrition between* is a dummy variable, which takes the value 1 if the respondent drops between waves, zero if otherwise. *Completehh_diary* takes value 1 if all the household members completed diaries, and zero if otherwise. Table 3 presents the factor

Table 3
Factor scores from factor analysis of attrition and completeness indicators.

Indicators	LV 1	LV 2	LV
Attrition within	0.13	**−0.89**	LV2: attrition
Attrition between	−0.54	**−0.58**	LV2: attrition
Number of completed questionnaires (based on waves)	**0.91**	0.03	LV1: completeness
Number of completed diaries per person	**0.71**	0.58	LV1: completeness
Number of waves household is complete	**0.85**	0.15	LV1: completeness
Complete household based on diary	0.09	**0.78**	LV2: attrition

scores from the factor analysis.

5. Modelling and results

The model specification was based on both descriptive statistics and literature review. Results for the choice model, latent variable (LV) and hybrid choice (HCM) models are shown in Table 4. To compare the consistency of the estimators, a set of parameters was estimated both separately (LV and DCM) and simultaneously (HCM).

5.1. Latent variable (LV) model for non-random attrition and completeness

In the latent variable model, we have two latent variables that were simultaneously estimated: attrition, both between and within, (LV2) and completeness of questionnaires and diaries (LV1). A set of variables was systematically tested in the latent variable model, examples being education, gender, age cohorts, gatekeeper-status, household size, number of children at home, perceptions on accessibility by car, public transport, bicycle and parking opportunities in the neighbourhood. However, not all of these variables were significant in the latent variable (LV) model.

Several variables were found to be relevant in explaining *attrition* and *completeness*. For example, gatekeepers are more likely to stay in the surveys, and to complete the questionnaires and diaries more adequately. Since, gatekeepers are the contact persons within the household, they probably feel more responsibility to stay. And, learning effects, which have a positive impact in reporting trips (see for example Axhausen et al. (2007), might be stronger for gatekeepers. Similarly, being head of the household also decreases the probability of dropping out in the next waves. Highly educated respondents were also found to have completed the questionnaires and diaries more properly than others.

The results also show that larger household size, number of children living at home and number of cars at home increase the probability of dropping out between surveys and completing fewer questionnaires.

5.2. Discrete choice model for trip rates

In the estimation of trip rates, the reference alternatives were 3 and 4, variables were included in alternatives 1 and 2. Table 4 shows the alternative specific parameters when best goodness fit, generic parameters were estimated otherwise. In the following sections, the results are discussed as individual and household level, survey methods and spatial level and panel effects.

5.2.1. Individual and household level: Socioeconomic characteristics, lifestyle and preferences

Looking at socio-demographic variables, both females and teenagers report fewer days with zero to two trips, which is probably due to responsibilities with maintenance activities, consistent with van Wissen (1991). Furthermore, respondents with a driving license have higher trip rates, probably because they are in charge of more household activities (e.g. pick-ups, drop-offs, etc.). Also, the results show that higher educated and employed respondents undertake more trips. Furthermore, people with children under 11 years old travel more often. Children below 12 need a companion for their activities, thus increasing the number of trips of the household. Consistent with the expectations, having a driver license positively influences the number of trips reported per day.

Regarding the life events, just two life events affect trip rates, i.e. a change in working hours and the birth of a child. Particularly childbirth decreases the number of trips of household members, in short term, and in comparison to households where no children are born, consistent with (van Wissen, 1991).

In our sample, using the internet for shopping was a significant factor in low mobility rates. This result contrasts Francke and Visser (2015), who found that impacts of online shopping, transport have remained limited until now. When it comes to changes in preferences, the results show that dynamics on preferred transport modes are a source of explanation for trip rates.[2] People who changed the preferred transport mode for work tend to undertake more trips. Particularly, the clearest change in preferences in our sample is an increasing preference for bicycle use.

[2] The respondents were asked about their preferred transport mode to work. The difference in preferences was measured between waves, see the parameter β_{change}.

Table 4
Results for LV, DCM and HCM model.[*]

	Name	Affected Alternative	LV model Value	LV model *t*-test	DCM Model Value	DCM Model *t*-test	HCM model Value	HCM model *t*-test
Latent variable model	$L_{meanAtt1}$: *constant latent variable*	*Completeness*	2.45	**79.37**			2.09	**53.37**
	$L_{meanAtt2}$: *constant latent variable*	*Attrition*	0.61	**101.03**			0.71	**67.81**
	$\lambda_{genderLV2}$: *gender is female*	*Attrition*	0.01	**2.24**			0.01	**1.87**
	λ_{HEADHH}: *head of household (1-yes, 0-otherwise)*	*Attrition*	0.00	1.04			0.01	1.49
	$\lambda_{education_{HIGH_{LV1}}}$ *(kader- en beroepsgerichte leerweg)*	*Completeness*	0.08	**10.29**			0.11	**12.03**
	$\lambda_{employment}$: *respondent is employed, with a fixed schedule*	*Completeness*	−0.01	−0.82			−0.02	**−1.81**
	$\lambda_{GATEKEEPERLV1}$: *respondent is a gatekeeper*	*Completeness*	0.06	**20.85**			0.09	**15.47**
	$\lambda_{GATEKEEPERLV2}$: *respondent is a gatekeeper*	*Attrition*	−0.05	**−6.77**			−0.08	**−8.59**
	$\lambda_{Householdsize_2}$	*Completeness*	−0.52	**−59.02**			−0.51	**−52.15**
	$\lambda_{Householdsize_2}$: *household size of respondent is equal to 2*	*Attrition*	−0.08	**−23.43**			−0.12	**−20.97**
	$\lambda_{NKIND_{LV1}}$: *no children living at home*	*Completeness*	−0.14	**−13.58**			−0.12	**−10.33**
	λ_{NKIND2}: *no children living at home*	*Attrition*	−0.05	**−14.15**			−0.07	**−11.10**
	λ_{HHAUTO_N}: *number of cars in household > 2*	*Completeness*	−0.12	**−7.33**			0.02	**1.97**
	λ_{HHAUTO_N}: *number of cars in household > 2*	*Attrition*	0.01	**1.92**			−0.12	**−6.56**
	β_{income}: yearly gross income higher than minimum (> 5.000)	*Completeness*	0.14	**4.97**			0.20	**5.23**
	α_{12} *Completehh_quest_sum*	*Completeness*					0.16	**21.01**
	α_{13} *n_quest*	*Completeness*					0.16	**21.02**
	σ_{11}: *n_diary*	*Completeness*	−0.33	**−122.36**			−0.28	**−56.96**
	σ_{12}: *Completehh_quest_sum*	*Completeness*	−0.25	**−65.44**			−0.19	**−37.51**
	σ_{13}: *n_quest*	*Completeness*	−0.25	**−70.63**			−0.19	**−38.69**
	σ_{21}: *Attrition within*	*Attrition*	−0.34	**−84.30**			−0.30	**−61.32**
	σ_{22} *Attrition between*	*Attrition*	−0.64	**−427.89**			−0.64	**−124.23**
	σ_{23} *Completehh_diary*	*Attrition*	−0.77	**−336.02**			−0.83	**−151.61**
	Discrete choice model for mobility rates							
	ASC_0 *constant 0 trips*	*0 trips*			2.51	**23.91**	2.09	**7.08**
	ASC_1 *constant 1–2 trips*	*1–2 trips*			2.17	**29.05**	2.09	**11.57**
	ASC_2 *constant 3–4 trips*	*3–4 trips*			0.71	**23.69**	0.71	**23.57**
	ASC_3 *constant > 4 trips reference*	*> 4 trips*						
	$\beta LV1$: *Latent Variable completeness*	*0 trips*					−1.20	**−6.08**
		1–2 trips					−1.06	**−9.19**
		3–4 trips					−0.83	**−7.92**
	$\beta LV2$: *Latent Variable attrition*	*0 trips*					2.77	**4.46**
		1–2 trips					3.27	**6.26**
		3–4 trips					2.81	**5.03**
Individual and household characteristics	$\beta_{AGE_{TEEN}}$: *zero to 17* years old	*0 trips*			−0.89	**−10.04**	−0.87	**−9.73**
	$\beta AGE_{ELDERLY}$: *respondent is 64 years old or over*	*0 trips*			−0.31	**−4.89**	−0.30	**−4.59**
		1–2 trips			−0.25	**−6.46**	−0.21	**−4.99**
	β_{gender} *respondent is female*	*0 trips, 1–2 trips*			−0.23	**−8.99**	−0.23	**−8.83**
	$\beta_{EDUCATION_{HIGH}}$: *education level is bachelor, master or doctor*	*0 trips*			−0.47	**−9.58**	−0.46	**−9.39**
		1–2 trips			−0.19	**−6.08**	−0.11	**−3.29**
	$\beta_{EDUCATION_{no}}$: no *education*	*0 trips*			−0.41	**−2.86**	−0.41	**−2.84**
	β_{income}: HH gross income is high (over 65.000 per year)	*0 trips*			−0.15	**−2.58**	−0.15	**−2.72**
		1–2 trips			−0.07	**−1.86**	−0.08	**−2.28**
	$\beta_{LICENSE_{both}}$: *possessing a driving license*	*0 trips, 1–2 trips*			−0.38	**−10.93**	−0.35	**−9.78**
	$\beta_{CHILD12}$: *Children < 12 years in household*	*0 trips, 1–2 trips*			−0.36	**−9.08**	−0.41	**−9.87**
	β_{CHILD6}: *Children < 6 years in household*	*0 trips, 1–2 trips*			−0.21	**−4.21**	−0.25	**−4.95**
	$\beta_{HHTYPE_{SINGLE_{CHILD}}}$: *household type is a single parent with child*	*0 trips*			0.07	0.87	0.03	0.41
		1–2 trips			−0.12	**−2.07**	−0.08	−1.45
	$\beta_{HHTYPE_{COUPLE}}$: *household type is a couple (without children)*	*0 trips*			−0.04	−0.70	−0.15	**−2.30**
	$\beta_{HHTYPE_{SINGLE}}$: *household type is a single parent*	*0 trips*			−0.31	**−4.93**	−0.39	**−5.64**
		1–2 trips			−0.32	**−8.59**	−0.23	**−5.53**
	β_{work}: *going to work more*	*0 trips*			−0.24	**−2.90**	−0.24	**−2.88**
	$\beta_{schedule}$: *change in work schedule*	*0 trips*			−0.22	**−5.64**	−0.22	**−5.61**
	β_{having}: *having a child*	*0 trips*			0.28	**2.69**	0.27	**2.59**

(continued on next page)

Table 4 *(continued)*

	Name	Affected Alternative	LV model Value	LV model *t*-test	DCM Model Value	DCM Model *t*-test	HCM model Value	HCM model *t*-test
		1–2 trips			0.14	**1.79**	0.13	**1.66**
	$\beta_{SHOP_{INTERNET}}$: *respondent shops online 4 or more days every week*	*0 trips*			0.18	**4.39**	0.18	**4.53**
	$\beta_{NOTWORKHOME_{cat0}}$: *respondent worked from home less than 12 h per week*	*0 trips*			−0.56	**−12.98**	−0.56	**−12.98**
	β_{change} *Change in preferred mode to work*	*0 trips*			−0.20	**−2.79**	−0.20	**−2.78**
Survey – related variables	β_{Weekday}: *trip diary belongs to working day (Monday to Friday)*	*0 trips*			−1.72	**−29.48**	−1.72	**−29.48**
					−0.58	**−13.87**	−0.58	**−13.90**
	β_{Friday}				−0.17	**−4.70**	−0.18	**−4.74**
	$\beta_{DAY_{6SAT}}$: *trip diary belongs to Saturday*	*0 trips*			−1.22	**−16.94**	−1.22	**−16.96**
		1–2 trips			−0.68	**−13.11**	−0.69	**−13.16**
	$\beta_{\text{First day}}$: *trip diary belongs to first day of survey*	*1–2 trips*			−0.12	**−4.47**	−0.12	**−4.49**
	β_{STAYER}: *Stayer 3 years; and 2014/2015*	*0 trips, 1–2 trips*			−0.32	**−10.36**	−0.31	**−9.82**
	β_{STAYER}: *Stayer 2 years consecutive (2013/2014/)*	*0 trips, 1–2 trips*			−0.17	**−3.74**	−0.15	**−3.39**
	β_{STAYER}: *Stayer non – consecutive 2013/2015*	*0 trips, 1–2 trips*			0.02	0.22	0.03	0.30
	$\beta_{OctoberNovember}$: *survey completed in October/Nov. Ref. September.*	*0 trips, 1–2 trips*			0.22	**5.18**	0.23	**5.34**
Spatial level	$\beta_{GOOD_{INFRA_{CAR}}}$: *valuation of accessibility by car is good or very good.*	*0 trips, 1–2 trips*			0.20	**5.18**	0.20	**5.20**
	$\beta_{GOOD_{INFRA_{PARK}}}$: *valuation of accessibility for parking is good or very good.*	*0 trips, 1–2 trips*			0.27	**6.27**	0.27	**6.13**
	$\beta_{GOOD_{PT}}$ *– Cat 1–2 trips. Valuation of accessibility by PT is good or very good.*	*0 trips, 1–2 trips*			0.14	**4.47**	0.13	**4.01**
	$\beta_{GOOD_{INFRA_{bike}}}$: *Valuation of accessibility bicycle is good or very good.*	*0 trips, 1–2 trips*			0.56	**8.29**	0.56	**8.17**
	$\beta_{LARGE_{CITY}}$: *respondent lives in a large city (Amsterdam, Rotterdam, Den Haag or Utrecht region)*	*0 trips, 1–2 trips*			0.31	**8.60**	0.30	**8.25**
	$\sigma\varphi_0$ *standard deviation*	*0 trips*			−0.11	**−3.15**	−0.10	**−2.88**
	$\sigma\varphi_2$ *standard deviation*	*1–2 trips*			−0.18	**−3.04**	−0.19	**−3.05**
	$\sigma\varphi_3$ *standard deviation*	*3–4 trips*			0.04	1.49	0.04	1.61
	$\sigma\varphi_4$ *standard deviation*	*> 4 trips*			−0.16	**−4.08**	−0.16	**−4.07**
	Number of draws				**250**		**250**	
	Rho squared		**0.57**		**0.40**		**0.44**	
	Sample size		**38 8684****					

* Variables in the choice model part are included in the alternatives 1 (zero trips/day) and/or 2 (1–2 trips/day), reference alternatives are 3 (3–4 trips/day) and 4 (> 4 trips/day).

** The unit of observations is number of trips per person/day, for each person 1–3 days were reported.

5.2.2. Survey methods

Regarding the survey characteristics, several data collection issues tend to affect the reported trips. For example, on the first day of the diary the respondents registered more trips. Golob and Meurs (1986) found a similar effect, caused most importantly by a day-to-day increase in the under-reporting of walking trips. Furthermore, the year of completing the survey significantly affects the trip rates. In general, the number of trips per day decreases every year. And, the number of respondents reporting zero-trip days increased over the years as well. The 'year of survey' can be associated with survey reminders and methods implemented in the last 2 waves (2014 and 2015).

Stayers have higher trip rates. In addition, stayers that participated in all waves have higher trip rates than stayers that participated in two waves, while they in turn have higher trip rates than the respondents that only participated one wave. From the magnitude of the parameters for different types of stayers (consecutive and non-consecutive years), we can observe that consecutive stayers have higher trip rates than *temporary drop-outs*. It also means that temporary attrition creates effects significantly different from those of permanent attrition. The results also show that more trips are undertaken during Sundays than Saturdays or weekdays (see also Table 2). These results are compatible with the findings of Golob and Meurs (1986), using the first wave of the former Dutch Mobility panel (in operation between 1984 and 1989) and also the Dutch National Travel Survey (CBS, 2015).

5.2.3. Spatial level

The perception of the neighbourhood accessibility by car and public transport (PT) is associated with higher trip rates.

Furthermore, people who state that their neighbourhood is well accessible by car and PT tend to report fewer zero-trips days. People living in big cities (e.g. Amsterdam, Utrecht, The Hague) are more likely to undertake at least 2 trips per day. This is an expected result, which can be associated to proximity and variety of places in high density cities.

5.2.4. Panel effects error components

The standard deviations of the error components (σ_φ) are statistically significant. This means that there is a significant correlation within respondents. There is a σ_φ parameter for each trip-rate category in the mixed logit model. The value of σ is larger for category 'zero trips'. It means that sociodemographic characteristics are very important when discussing immobility. However, when it comes to the 2nd (1–2 trips) and 3rd category (3–4 trips) the effects of sociodemographic characteristics are lower.

5.3. Hybrid choice model (HCM)

Table 4 shows the results for the simultaneous estimation for the DCM and LV models. As we can observe, the parameters in the LV section of the HCM model show very similar values to the LV model (left columns). It means that both models are consistent and came out with the expected magnitudes and signs. The HCM shows that the latent variables are statistically significant for modelling trip rates. And, the value of rho-squared shows that the HCM model is more robust than the DCM model.

Noticeably, the parameter for LV1 in category 1 is negative. It means that survey *completeness* at the household level is negatively associated with lower trip rates. Respondents who are part of a household in which (all) household members fully completed the questionnaires do not tend to report more trips on survey days (LV1). It can also indicate that respondents living in a household with more completed diaries (waves) are more mobile. In the HCM, the parameter for LV2 (attrition between and within) in category 1 is positive. It means that higher probabilities of attrition are shown by respondents with low trip rates. The parameter is in magnitude larger for the category 1–2 trips per person-day. Comparing the HCM and the DCM models, the main differences can be found in the survey related variables and standard deviations of error components. This shows that mixed logit model with full covariance includes all sources of correlation. For more details on the estimation of sources of correlation, see Hess and Train (2017). In this particular case, the correlation was given by attrition and completeness. However, the HCM allows to explicitly represent particular correlations. Furthermore, differences between parameters prove that attrition and completeness effects are highly influenced by survey methods, which is further investigated in the see next subsection.

5.3.1. Additional model estimations

Table 5 shows the parameters and goodness of fit for the additional estimations of the hybrid choice model with attrition/ completeness effects. As can be seen in Table 5, when the model is estimated per wave, completeness remains significant in 2013 and 2014, whereas attrition is less significant, or insignificant for zero trip category in the 95% confidence level. The most significant effect of (in)completeness is in 2013. This result can be associated with more committed refreshment sample in 2014.

When comparing this with the general model in Table 4, we observe that the findings for LV1 is still negative, i.e. the better the completeness rate, the lower the tendency to report zero trips. This result is very interesting and it is consistent among the additional

Table 5
Estimated parameters for latent variables and goodness of fit for additional model estimations.*

Additional models	Value	t-test**	Model Rho-square	Sample N
2013				
$\beta LV1$: *Latent Variable completeness (1–2 trips)*	−1.96	**−3.06**	0.52	11,919
$\beta LV2$: *Latent Variable attrition (zero trips)*	−2.65	−1.40		
$\beta LV2$: *Latent Variable attrition (1–2 trips)*	8.86	**2.14**		
2014				
$\beta LV1$: *Latent Variable completeness (1–2 trips)*	−0.30	**−2.75**	0.49	16,251
$\beta LV2$: *Latent Variable attrition (zero trips)*	−0.49	−0.32		
$\beta LV2$: *Latent Variable attrition (1–2 trips)*	2.02	1.42		
2015				
$\beta LV1$: *Latent Variable completeness (1–2 trips)*	−0.38	**−3.75**	0.48	26,949
$\beta LV2$: *Latent Variable attrition (zero trips)*	−1.52	−1.08		
$\beta LV2$: *Latent Variable attrition (1–2 trips)*	1.59	1.43		
Model for Gatekeepers (all waves)				
$\beta LV1$: *Latent Variable completeness (1–2 trips)*	−0.43	**−2.17**	0.44	17,169
$\beta LV2$: *Latent Variable attrition (zero trips)*	−0.05	−0.04		
Model for non-gatekeepers (all waves)				
$\beta LV1$: *Latent Variable completeness (1–2 trips)*	−0.735	**−2.36**	0.45	21,699
$\beta LV2$: *Latent Variable attrition (zero trips)*	−1.15	−1.48		

* A full model was estimated for each sample segment, but only the LV parameters are shown in this table.
** The estimated parameters of the LV are shown, even when there are not significant in the 95% confidence level in order to show the different results between waves.

Table 6
Average difference between probabilities, estimated from HCM and DCM models.

	Prob. 0 trips	Prob. 1–2 trips	Prob. 3–4 trips	Prob.4 trips+
Average probabilities HCM				
2013	17.9%	32.5%	29.3%	20.3%
2014	19.1%	34.6%	27.2%	19.1%
2015	19.1%	35.5%	26.7%	18.8%
Grand Total	18.7%	34.2%	27.7%	19.4%
Differences in probabilities between HCM and DCM				
Gatekeeper				
Non-gatekeeper	−1.09%	0.62%	0.40%	0.08%
Gatekeeper	0.87%	−0.53%	−0.30%	−0.05%
Grand Total	**0.0%**	**0.0%**	**0.0%**	**0.0%**
12–17	−0.02%	−0.57%	0.34%	0.25%
18–24	0.12%	−0.89%	0.46%	0.31%
25–34	0.02%	0.12%	−0.10%	−0.04%
35–44	−0.01%	0.15%	−0.09%	−0.04%
45–54	−0.04%	0.09%	−0.05%	0.00%
55–64	−0.01%	0.54%	−0.35%	−0.18%
65–74	0.04%	−0.04%	0.00%	0.01%
> 74 yr	0.05%	0.08%	−0.08%	−0.05%
Grand Total	**0.0%**	**0.00%**	**−0.02%**	**0.01%**
Car use				
4+/week	0.0%	−0.04%	0.01%	0.03%
1–3 days/week	0.0%	−0.03%	0.00%	0.02%
1–3 days/month	0.0%	0.16%	−0.12%	−0.06%
6–11 days/month	0.1%	0.28%	−0.25%	−0.11%
1–5 days/year	0.0%	0.42%	−0.28%	−0.15%
Never (less than 1 day/year)	0.0%	0.40%	−0.31%	−0.13%
Grand Total	**0.0%**	**0.00%**	**−0.02%**	**0.01%**

estimations. It means that, for every wave, low trip rates associated to low completeness. It is important to note that $\beta LV1$ is larger in the non-gatekeepers model than in the gatekeepers model. It indicates a stronger tendency of non-gatekeepers to not fully complete their diaries or report zero trips.

The goodness of fit of the models is analysed as rho-squared corrected, to account for the differences in terms of number of estimated parameters (Ortúzar and Willumsen, 2011). As can be seen, for wave 2014 the rho-squared corrected is lower (0.49) than the goodness of fit for the wave 2013 (0.52). Both completeness and attrition effects are larger in 2013 than 2014, or the combined responses of 2014 and 2015. As can be seen, long-term runs tend to stabilize the sample.[3]

The same model specification was implemented for gatekeepers and non-keepers. As can be seen in Table 5, in the model for gatekeepers, both latent variables lost significance, and the LV2 (attrition) was insignificant. It means that trips reported by gatekeepers are not influenced by attrition, and incompleteness effects are very weak.

6. Model applications

A common test of differences between HCM and DCM is the estimation of probabilities. Policy recommendations are commonly based on demand forecasting. This means that via this test, researchers can quantify the level of influence of the latent variables on policy recommendations. Comparison of forecast between DCM and HCM is common practice in the modelling field. See for example, Yáñez et al. (2010b) and Glerum et al. (2014).

We calculate the weights between the HCM and DCM models, meaning the differences in probabilities by categories, before and after including the attrition/completeness effects. The differences in probabilities are shown in Table 6. The differences in probabilities are shown for different groups that were found to display 'relevant' differences. As we can observe, the effects are very small in relative values. The differences between HCM and DCM probabilities do not exceed 1% for the majority of the groups. These findings can be related to the large sample size: we are dealing with almost 40,000 observations. Larger samples tend to asymptotically efficient parameters. Also, it is important to note that in choice models the alternative specific constants (ASC) absorb the lack of information due to absence of explanatory variables. Therefore, the ASCs are less significant in the HCM model, and the LV model shows the source of explanation, which is not present in the DCM.

The estimated probabilities show that on average 18% of respondents in our sample reported no trips, while 34% undertake 1–2 trips per day; 27% undertake 3–4, and 19% more than 4 trips. This is consistent with previous findings which suggested that a short reference period would have a larger zero-trips share (Madre et al., 2007). Compared with, for example, 7 days of reporting trips,

[3] The Log-likelihood is not discussed because the models have different sample sizes; therefore, the Log-likelihood is not comparable.

3 days is a short reporting period. It is also consistent with an important issue in panel data found in Cantillo et al. (2007): the presence of habit or inertia in choice-making behaviour.

As can be seen in Table 6, the largest biases are frequently observed in the first 2 categories of trips (0 trips, 1–2 trips). It means that attrition affects more the lowest trip rate levels. Particularly, teenagers introduce the largest bias in the sample, whereas frequent car users seem to bring more stability to the panel, which can be associated with the habit of using the car and undertaking a consistent number of trips per day.

In summary, the model applications show that panel attrition and survey completeness bias occur in the first three waves of the Netherlands Mobility Panel. However, these biases are very small because of the large sample size. This implies that there is no real need to weigh the sample to control for attrition effects. However, the source of the attrition can be identified via the latent variable model, and therefore this bias can be controlled.

7. Conclusions

This paper provided the first application of hybrid choice models to examine non-random attrition and mobility rates, using trip diaries data from the Netherlands Mobility Panel (MPN). The Hybrid choice model comprises two parts which allow the identification of attrition biases at the individual level, i.e. a discrete choice part representing categories of trips, and a latent variable part comprising two latent variables for non-random attrition (attrition and completeness). Main conclusions attain travel behaviour over time, panel data collection, modelling and applications can be derived, as follows:

Firstly, from the point of view of travel behaviour and data collection over time, the results show that intrapersonal trip rates vary significantly by year, week and day of the week. In despite of other data collection methods can be used to capture intrapersonal variation in a larger scale, e.g. GPS tracked data. The present paper illustrates the importance of conducting multi-day panel studies to understand the temporal dynamics in travel behaviour; which are not captured in one-day cross-sectional travel surveys typically used around the world. Furthermore, since trip rates are the base for explaining travel behaviour, this paper shows the relevance of considering attrition and completeness effects when modelling travel behaviour. The paper has also proved that attrition effects significantly vary across waves.

Secondly, concerning the modelling of panel data, we have learned that both *attrition* and *completeness* are statistically significant in estimating mobility. The paper has shown the source of attrition, by explaining latent effects with explanatory (socioeconomic) variables. Also, socioeconomic variables (gender, driving license, household type and size), mode preferences, spatial infrastructure and life events highly influence mobility rates, even after controlling for attrition effects. The estimation of probabilities for both DCM and HCM showed that differences between HCM and DCM probabilities considering the three MPN waves are relatively small (less than 1%). There are however significant differences in attrition effects between groups. In the three waves that were covered, stayers have consistently higher trip rates than drop-outs. Gatekeepers show less propensity to leave the survey. This implies that stayers and gatekeepers are more accurate at keeping their trip diaries and drop-outs tend to underreport the trips. In addition, attrition is associated with the level of completeness at the household level.

Finally, a relevant application of this HCM model related to panel data collection, would be the estimation of scenarios based on the LV variables to predict attrition and its effect on the choice model. Scenarios can be performed and differences in probabilities can be estimated see for more discussion Chorus and Kroesen (2014).

As this paper provided the first application of hybrid choice models to examine non-random attrition and mobility rates, there are several directions for future research. Firstly, research can be done to verify the causality-effects between attrition bias, survey completeness and reporting of infrequent trips in the MPN, which are likely to be underrepresented in trip diaries. Secondly, more precise mode choice models can be developed considering the attrition effects. More specifically, it is interesting to verify whether certain (negative or positive) attitudes towards specific transport modes influence the completeness or reporting process. Thirdly, as the MPN will continue for several years, it is interesting to conduct the analysis using additional waves, and verify the simultaneous attrition and completeness effects over longer period of time.

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