EJTIR

Issue 16(4), 2016
pp. 698-712
ISSN: 1567-7141
tlo.tbm.tudelft.nl/ejtir

Exploring the impact of household interactions on car use for home-based tours: a multilevel analysis of mode choice using data from the first two waves of the Netherlands Mobility Panel

Marie-José Olde Kalter[1]
Goudappel Coffeng, Deventer, the Netherlands.

Karst T. Geurs[2]
University of Twente, Enschede, the Netherlands.

While most studies on mode choice behaviour and households are typically based on individual travel behaviour decisions, less is known about how relations inside households affect mode choice. This paper addresses this topic by examining intra- and inter-household variation in car use. The decision to use the car is modelled for home-based tours, based on data from the 2013 and 2014 waves of the Netherlands Mobility Panel. A multilevel framework is used to investigate mode choice behaviour at tour, individual and household level to account for the impact of individual and household characteristics on travel mode choice, interdependencies of individuals within their households and variation in individual travel mode choice and other characteristics over time. The results show that variability between households and individuals accounts for more than one third of the total variation in the mode choice of home-based tours. In dual-income households, intra-household interactions have a larger effect on car use than inter-household interactions. Although only two panel waves are used, the model results show significant time effects on mode choice: if the same tour was also conducted in the previous year and one person changed working hours or work location, car use is less likely.

Keywords: *household interactions, travel behaviour, multilevel analysis, panel data, car use.*

1. Introduction

The overarching aim of transport policies in most countries is to increase accessibility and at the same time reduce the externalities created by transport. To achieve these aims, transport policies are developed and implemented to promote a modal shift from car use towards more sustainable modes such as public transport, cycling and walking. Knowledge about the factors that determine mode choice is therefore essential, and this has been a major topic in travel behaviour research in recent decades. There is a huge body of literature on mode choice behaviour. However, like other activity-travel behaviour studies, most of these studies are typically based on individual travel behaviour decisions. The existence of intra-household interactions giving rise to joint activity participation and interdependencies in travel decisions has long been acknowledged, yet empirical studies of household interactions still remain limited (Ho and Mulley, 2015a).

There are numerous facets to intra-household interactions and group decision-making that have important implications for mode choice behaviour. For instance, in a multi-driver household with

[1] A: P.O. Box 161, 7400 AD Deventer, the Netherlands T: +31 570 666 252 E: moldekalter@goudappel.nl
[2] A: P.O. Box 217, 7500 AE Enschede, the Netherlands T: +31 53 489 1056 E: k.t.geurs@utwente.nl

only one car available, agreements about car use have to be made. Also, time-varying personal or household-level factors may influence household interactions and affect travel behaviour. Important life events, such as changing jobs or having children, can prompt reconsideration of routine behaviours, break habits and form a trigger for changes in travel behaviour (Bamberg et al., 2003). Probably because of the lack of panel data, most studies on household interactions and travel behaviour (see Ho and Mulley (2015a) for an overview) do not take changes in individual or household characteristics into account.

Bhat and Pendyala (2005) concluded that there has been a great leap forward in understanding and modelling intra-household interactions and group decision-making. However, much remains to be explored and learnt. In particular, there is little literature about the impact of household interactions on travel mode choice, with the work by Miller et al. (2005) and Ho and Mulley (2013, 2015b) among the few recent studies. Ho and Mulley (2015b) found that mode choices differ significantly across joint tour patterns, with public transport being less likely to be used for joint travel. Miller et al. (2005) developed a disaggregated tour-based mode choice model, which predicts the mode choice of individual trip makers and takes within-household and inter-personal interactions into account. However, most studies investigate interdependencies between household members by defining household characteristics at the individual level, like household size or the number of children.

An examination of the existing research shows that less is known about how relations inside households affect mode choice. Consequently, there is little knowledge about which part of variation in mode choice is due to differences among households and which part is due to interactions between household members. In this paper, we examine intra- and inter-household variation in mode choice. We used data from the first two waves from the Netherlands Mobility Panel (in Dutch: Mobiliteitspanel Nederland, MPN). The MPN is specifically designed for examining changes in travel behaviour, both at the individual and the household level and the analysis in this paper addresses the following research question: *to what extent do household interactions affect home-based car tours, and how do changes in household and individual characteristics affect home-based car tours?*

The remainder of this paper is organised as follows. Section 2 provides a short review of the literature on the influence of household interactions on travel behaviour. Section 3 describes the methodology and data used for the analysis. Section 4 details the estimation results and Section 5 presents the conclusions and discusses directions for further research.

2. Literature on household interactions and travel behaviour

Most research on mode choice behaviour is based on individual behaviour and, therefore, on the individual decision-making process. In general, research on mode choice behaviour focuses on the following group of determinants at the personal level: individual and household characteristics, attitudes and preferences, built-environment variables and trip characteristics (Olde Kalter et al, 2014). Although the importance of representing group decision-making mechanisms of household behaviour has been recognised since the 1980s, studies about group behaviour in transportation are new and remain limited (Timmermans and Zhang, 2009).

Household interactions can be divided in three main categories: resource and allocation usage, task and time allocation, and joint-activity allocation (Timmermans, 2009). All three categories have their own effect on travel behaviour. With regards to the first category (resource and allocation usage), some households may have limited resources (for example, one car in a multi-driver household), which in turn can affect individual travel patterns. Most studies that take resource and allocation usage into account focus on the relationship between car ownership and/or car availability and mode choice (for example Anggraini et al., 2008; Gliebe and

Koppelman, 2005). Maat and Timmermans (2009) examined whether the decision to commute by car is influenced by built-environment characteristics, taking interdependencies between household partners into account. They found that for cases of dual earners with only one car, the partner with the greatest commuting distance and the lowest-density work location is likeliest to commute by car.

Task and time allocation decisions may also affect travel behaviour. Not all (household) tasks have to be carried out by all household members, such as grocery shopping and taking the children to school. Ettema et al. (2007) investigated the role of location factors in task and time allocation at the household level. The results of that study indicate the existence of various intra- and interpersonal linkages in activity choice and time allocation. Wang and Li (2009) developed a model of time allocation in a household and found that time allocation of males contributes more heavily to household utilities than time allocation of females and that optimal time allocation patterns depend on household income, number of children, car ownership and type of housing. Schwanen et al. (2007) investigated the distribution of out-of-home household tasks between spouses. The results show that women perform the bulk of out-of-home household activities and that the distribution of household tasks between partners is more even in higher-density, higher-diversity neighbourhoods.

Concerning joint-activity allocation, decisions about joint activities will have a synchronising effect on the activity and travel patterns of household members. Vovsha, Petersen and Donnelly (2007) found that joint travel constitutes a significant share (40-50 percent) of total travel. Ho and Mulley (2013) established that joint household travel accounts for about 60 percent of all home-based tours at weekends and for about 50 percent on weekdays. They also showed that arrangements of joint household travel are highly associated with travel purpose, social and mobility constraints and household resources. Especially the presence of children is important in household interactions and joint travel. Vovsha and Petersen (2005) and Yarlagadda and Srinivasan (2008) found that chauffeur characteristics (gender, employment status and age), the children's ages, household car ownership, household income and relative distance between home, school and workplace had a significant effect on the decision about who takes the children to school.

The present paper contributes to the understanding of the effect that (changes in) relations between household members has on travel mode choice, with a special focus on joint activities by household members as well as with non-household members. Our expectation was that mode choice is not only the outcome of individual decisions. Our analysis of how relations between household members affect car use also addresses the effects of different household types and changes in individual and household characteristics on mode choice.

3. Methodology

A multilevel binary logit model was developed to examine the impact of interactions between household members on car use. We used a binary mode choice variable as dependent variable: auto driver mode (1) and other means of transport (0). We decided to use a binary mode choice model as we were interested in the effect of household interactions and the influence of changes in household interactions on the decisions of household members to drive a car or not to drive a car. The results of the model serve as a starting point for investigating more complicated mode choice models in follow-up studies.

3.1 Multilevel analysis

It is fair to expect that individual household members interact with each other, meaning that individual persons are influenced by the household to which they belong. Although it is generally known that individuals within a specific household type may have different travel patterns, most research does not take these differences into account. A common specification error in travel behaviour research is that variables at the household level, for example household size and car availability, are disaggregated into explanatory variables at the individual level. The opposite occurs as well; sometimes individual characteristics are aggregated to explain differences between households, for instance by assigning to a household the mean trip rate for all household members. Disaggregation and aggregation causes incorrect assumptions of independence at different levels. Multilevel analysis is one of the best approaches to deal with this variation at different levels.

In multilevel analysis, the grouping of participants, which results from either the sampling scheme (for example, selection of neighbourhoods followed by selection of individuals within neighbourhoods) or the social groupings of participants (for example, being in the same classroom, department, organization or political district), is the focus of the theory and conceptual model, as proposed by Kreft and De Leeuw (1998). Multilevel analysis is a suitable approach for taking the *social contexts* as well as the *individual respondents* or *subjects* into account. Multilevel analysis is a statistical technique, which can be applied to hierarchical nested data. Multilevel models open up opportunities not only to examine relationships at multiple levels of a data hierarchy but also to incorporate a time dimension into the analysis. Longitudinal data, or repeated measures data, can be viewed as multilevel data, with repeated measurements nested within individuals (Hox, 2010). However, at least three time points are required to model patterns of change over time (Liu, 2016).

Multilevel analysis carried out in relation to travel behaviour falls into two categories of approach (Lipps and Kunert, 2005). The first approach takes the hierarchy in the data into account. Most of these studies focus on the relation between travel behaviour and spatial factors. For example, Schwanen et al. (2004) investigated the impact of metropolitan structure on commute behaviour of urban residents in the Netherlands. In this study, multilevel regression was applied to allow for interdependencies among a variety of levels of analysis ranging from the individual worker to the metropolitan region. The results show that the variation in mode choice among individual workers *within* residential zones is much larger than the variation *between* such geographical units. Another example comes from the work by Borgoni et al. (2002). They focused on the influences of household characteristics and one regional variable on car ownership and use and concluded that there exists some regional clustering of specific household types in Austria. Klockner and Friedrichsmeier (2011) used a two-level structural equation model to model the decision to use the car in contrast with alternative travel modes. This brief analysis shows that the multi-level approach adds information about interactions between both the levels and the amounts of variance present at each level.

The second approach regarding multilevel analysis accounts for repeated measurements from longitudinal surveys with a nested structure at the individual or household level. In this way, multilevel analysis helps understand the individual variation of travel behaviour. To the authors' knowledge, the literature contains only one longitudinal study concerning household interactions. Goulias (2000) used data from the first five waves of the Puget Sound Panel Survey, the first general-purpose travel panel survey in the United States, which was in operation between 1989-2002 and comprised 1,700 households. Goulias (2000) examined not only the variation between persons and households, but also the variation in travel behaviour over several years. The most important findings in the analysis are the large variance contributions by each level and the lack of symmetry in change over time. Another example of the use of a time variable in multilevel analysis is the study of Cherci and Cirillo (2008). They estimated a mode choice model that accounts for systematic and random heterogeneity over individual preferences and responses and correlation across individuals over three time periods. The results of that study show that accounting for correlation between individuals in panel data improves model results enormously. In another study, Cherci and Cirillo (2014) used a six-week travel diary survey to study the intrinsic variability in the individual preferences for mode choices, the effect of long-term plans and habitual behaviour in daily mode choices. They found that there is a strong inertia effect in mode choice that increases with (or is reinforced by) the number of times the same tour is repeated.

3.2 *Model specification*

The multilevel framework allows us to investigate mode choice behaviour at different levels. In this study, we decomposed the total variation in car use into variations at three different levels: household level, individual level and tour level[3]:

1. Tours form the first level at which the dependent variable (car use) is measured.
2. The second level is taken up by the individuals within the households.
3. The households represent the third level. This is the basic unit of demand in which activities are organised, budgets and goods (for example, cars) are shared, similar attitudes are prevalent and the socio-economic status of the members is generally comparable (Lipps and Kunert, 2005).

We created explanatory variables for each level (see Table 1). These variables served to explain the variation in car use between and within different individuals and households. Different explanatory variables from the common group of determinants (individual and household characteristics, attitudes and preferences, built environment and trip characteristics) and also variables related to ICT use were tested. Only variables that showed a statistically significant effect or variables that are related to household interactions were included in the final model. For this reason, for example ICT use such as telework was excluded. Previous analyses with MPN data showed a significant effect of ICT use on commuting mode choice (see Olde Kalter et al., 2014). By contrast, ICT use is not a significant variable in the present study, probably because all trip purposes were included.

Table 1. Explanatory variables for different levels

Level	Explanatory variables
1 – Tours	Purpose
	Distance
	Joint activity
	Accessibility of destination
	Same tour in 2013
	Same tour in 2014
2 – Individuals	PT season ticket holder
	Car licence holder
	Preference for cycling (for different purposes)
	Changed working hours
	Changed work location
	Changed preference for car use
3 – Household	Children <12 years in household
	Car availability
	Single-income or dual-income households

A multilevel model consists of a fixed part and a random part. The *fixed* part represents the systematic relationship between the dependent variable and explanatory variables at different levels. For example, at level 1 (tour level), car use may be affected by main purpose and distance. At level 2 (individual level), variability in car use can be the result of differences in preference. At

[3] We also examined a fourth level: municipality of the home location. Probably because of the small number of households within each municipality, this level showed no significant effect and was therefore omitted from the study.

level 3 (household level) the focus is on differences between various household structures, for example single-income or dual-income households. The *random* part allows for variation around this fixed part (Bullen, Jones and Duncan, 1997).

Because our dependent variable is discrete, we specified a generalised linear model consisting of a set of linear predictors and a nonlinear link function, with is typically a logit function in the case of a binary response variable. The resulting model is the multilevel equivalent of the traditional logistic regression or logit model. The level-1 model for mode choice of a tour η_{ijk} as outcome variable and tour i nested in individual j and household k with one explanatory variable X_{ij} is of the general form:

$$\eta_{ijk} = \log\left(\frac{\pi_{ijk}}{1-\pi_{ijk}}\right) = \beta_{0jk} + \beta_{1jk}X_{ij} \tag{1}$$

No residual variance term is included for level 1 because the underlying probability distribution associated with η_{ijk} is not normally distributed. For level 2, we specified an individual variable W_{jk} (individual *j* within household *k)*:

$$\beta_{0jk} = \gamma_{00k} + \gamma_{01k}W_{jk} + \mu_{0jk} \tag{2}$$

For level 3, we specified a household covariate:

$$\gamma_{00k} = \gamma_{000} + \gamma_{001}Z_k + \mu_{00k} \tag{3}$$

We also specified the tour level predictors as fixed at level 2 ($\beta_{1jk}=\gamma_{10k}$) and individual-level predictors to be fixed at level 3 ($\gamma_{01k}=\gamma_{010}$). The μ-terms are (random) residual-error terms at the individual and household level. These residual errors are assumed to have a mean value of zero. Combining this information into a single equation gives:

$$\eta_{ijk} = \gamma_{000} + \gamma_{100}X_{ij} + \gamma_{010}W_{jk} + \gamma_{001}Z_k + \mu_{00k} + \mu_{0jk} \tag{4}$$

If there are no explanatory variables at the tour, individual and household level, Eq. (4) reduces to:

$$\eta_{ijk} = \gamma_{000} + \mu_{00k} + \mu_{ojk} \tag{5}$$

This is the so-called intercept-only or unconditional model, where γ_{000} represents the intercept at household level, μ_{00k} represents the household level random effect for the intercept, and μ_{ojk} represents the random effect for intercepts at individual level. The intercept-only model can be used to produce an estimate of the intra-class correlation ρ. This parameter tells us if the probability of choosing the car is generally more alike for household members than for non-household members, which violates the assumption of independence of all observations (Hox, 2010). The intra-class correlation describes the proportion of variance that lies between households and individuals ($\sigma^2_{between}$) relative to the total variance ($\sigma^2_{between}+\sigma^2_{within}$). We can define the intra-class correlation ρ of a logistic distribution, as follows (Hox, 2002; Hedeker, 2007):

$$\rho = \frac{\sigma^2_{between}}{\sigma^2_{between} + \frac{\pi^2}{3}} \tag{6}$$

To investigate the variation in car use at the household and individual level, we estimated different multilevel models. We started with an intercept-only model (M1), to examine the extent of variability of car use across individuals (level 2) and households (level 3). Next, we estimated a full model with fixed and random effects at each level (M2). To gain a better understanding of the interactions between household members within different household types, we estimated two models. We selected all multiple-person households with single and dual incomes (M3), and developed a separate model for dual-income households only (M4). As our main objective was to examine to which extent interactions between household members affect car use, we also added a random 'slope' effect to the models to investigate the variation between households in the influence of joint activity patterns on mode choice.

3.3 Data

The analyses in this paper are based on data from the first and second wave of the MPN. Socio-economic attributes for households and their members were collected for each household through individual questionnaires. Participants with a completed questionnaire were invited to keep a three-day online trip diary for three successive days (including weekend days). 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 in other travel-related factors (for example economic crisis, reduced taxes on sustainable transport or changes in land use) correlate with (changes in) travel behaviour. The publication by Hoogendoorn-Lanser et al. (2015) contains a description of the overall set-up and design of the MPN and of the philosophy behind the innovative design approach of the MPN's web-based diary.

In the present paper, *home-based tours* are the unit of analysis. All trips with home as starting and end point form one tour. Every trip, called a trip segment, is considered one part of a tour. If one or more trip segments are made jointly, with one or more other persons, we speak of a joint tour. A joint tour can be made 'fully joint' (two or more persons travelling together, leaving home and returning together) or 'partly joint' (two or more persons travelling together, but leaving home or returning separately). A distinction is made between tours with household members and tours with non-household members. Each tour is assigned a main purpose based on a hierarchy, in which work has the highest priority, followed by education, shopping and personal services, and social and leisure, after Stopher et al. (1996). Similarly, tours involving more than one travel mode are assigned a main mode, which is the mode with the highest share of travel time.

Only 'frequent' daily trips were selected, which means that holiday trips, trips abroad and occupational trips were excluded. Also, we only included individuals aged over 17 (the age at which it is legal to drive a car in the Netherlands) in the analysis. From other analyses (see for example Ho and Mulley, 2013), we know that travel mode choice and joint activities are very different at weekends. Other research also shows that these differences cannot easily be captured in one model by using weekday dummies (see Kloas and Kunert, 1994; Chlond and Lipps, 2000). Therefore, we restricted our analysis to working days (Monday to Friday) and to persons who reported at least one tour on one of these days. As we were interested in intra-household interactions, we selected only 'complete' multiple-person households. 'Complete' means that *each* household member completed the travel diary. This gave us the ability to distinguish between tours accompanied by household members and tours accompanied by non-household members. Finally, we selected all individuals who participated in the first and second wave. In total, we used data from 514 households and 960 individuals. The final dataset consists of 3,266 home-based tours in 2014 and 3,343 home-based tours in 2013. The 2104 dataset served as baseline in the analysis.

Repeated tours may indicate a preference for specific travel modes (Yang and Timmermans, 2015). To examine the impact of repeating tours, two variables were constructed, namely a variable that measures if the same home-based tour occurred in the previous year and a variable that measures if the same home-based tour occurred on another day in the same year. Furthermore, we constructed several 'change' variables to examine the effect of changes between 2013 and 2014 in individual, household and spatial characteristics. Several life events were also included in the analysis.

3.4 Sample description

Table 2 shows car use, according to the selected sample, by various tour and individual characteristics. Of all home-based tours considered, 48 percent were made by car in 2014. The average distance of a home-based tour by car is 33.9 kilometres. The average distance travelled by public transport is 81.4 kilometres, and 4.7 kilometres for cycling or walking. The average distance of all other modes together is 11.2 kilometres. Work and business tours have by far the highest share of car use (60 percent), while fewer than half of all tours for other purposes were made by car. This suggests that particularly in dual-income households with one car, where both workers would like to use the car for commuting, agreements on car use are necessary. To examine the impact of spatial characteristics, we used a variable commonly used in urban planning in the Netherlands, representing the accessibility typology of trip destinations. (Hilbers et al., 2005). Typology depends on the location relative to public transport facilities and access to a highway (see Table 3). A-locations are easily accessible by public transport, regardless of their distance to a highway, and consequently have the lowest share of car use (35 percent). C-locations, not easily accessible by public transport but close to a highway, have the highest share of car use. Furthermore, Table 2 indicates no great differences between 2013 and 2014 in tour and individual characteristics, probably because of the relatively short time period. These changes are therefore not used in explaining variation in car use.

Table 2. Car use by tour and individual characteristics

Level	Variable	Values	2013	2014
Home-based tour (n=3,266)	Distance tour (km)	Mean distance car	34.9	33.9
		Mean other modes	11.4	11.2
	Purpose tour (%)	Work, business	64	60
		Education	43	49
		Shopping and personal services	50	47
		Social and leisure	41	40
	Accessibility of destination (%)	A-location	43	35
		B-location	52	53
		C-location	55	54
		D-location	48	43
		R-location	50	49
Individual (n=960)	PT season ticket holder	No	62	56
		Yes	31	32
	Car licence holder	No	13	10
		Yes	58	54

Table 3. Typology of accessibility

	Distance to highway < 2 km	Distance to highway >2 km
Distance to main railway station < 3 km	A	A
Distance to secondary railway station < 2 km or metro < 1 km	B	D
Other	C	R

Table 4 shows household characteristics of the sample. Of all households considered, 51 percent always have a car available. This means that the number of cars in the household is the same as or greater than the number of persons with a driving licence in the household. The majority have no children younger than 12 years old. Single- and dual-income households have a higher share of car use than no-income households (i.e. none of the household members have income from paid employment or self-employment). Also, at the household level, we see hardly any differences between 2013 and 2014.

Table 4. Household characteristics (%)

Level	Variable	Values	2013	2014
Household	Car availability	Not always car available	47	49
(n=514)		Always car available	53	51
	Children <12 years	No	70	71
		Yes	30	29
	Income type	No-income household	25	25
		Single-income household	27	30
		Dual-income household	49	45

Joint-activity patterns

As our focus is the effect of household interactions on car use, we take a closer look at joint-activity patterns. Table 5 compares individual and joint tours for different travel purposes. Most work and business tours are individual tours (76 percent), whereas shopping and personal service, and social and leisure tours are more likely to be joint tours. The latter two are also more frequently undertaken with a household member (more than 30 percent), while educational tours are more likely to be accompanied by non-household members (27 percent).

Table 5. Distribution of joint tours (%) by purpose in 2014

Tour type	Work, business	Education	Shopping and personal services	Social and leisure
Individual	76	57	51	43
Fully joint with hh	1	13	23	17
Fully joint without hh	4	19	11	11
Partly joint with hh	9	3	9	16
Partly joint without hh	10	8	5	13

Figure 1 shows the share of joint tours by car. Most joint tours are made by car, with the highest share for fully joint tours with a household member (64 percent). Individual tours are more frequently undertaken by other means of transport. This suggests that travelling together and joint activities increase car use. Fully joint tours have a larger share of car use compared with partly joint tours, although the difference between fully joint tours with non-household members and partly joint tours with household members is small.

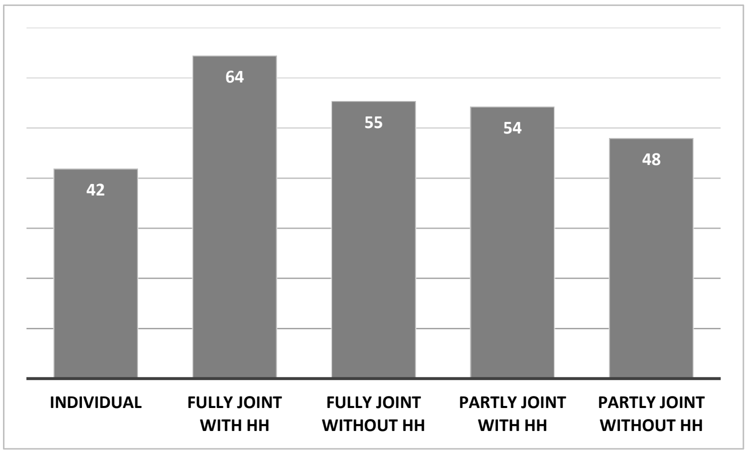

Figure 1. Share of joint tours (%) by car in 2014

Changes in individual, household and spatial characteristics and life events

The analysis presented in this paper concerns the 2013 and 2014 waves of the MPN. As this is a relatively short period of time, there are no major changes in individual and household characteristics at the aggregate level, as expected. For example, only 6 percent of the households increased in size and about 4 percent had a lower income in 2014. The accessibility type of the residential locations obviously didn't change much for the sample either, although the perceived accessibility of the living environment by car, public transport and bicycle on individual level was more positive in 2014. The greatest changes occurred in the stated mode preferences. Individual respondents were asked to state their preferred mode(s) of transport for specific trip motives (i.e. commuting, business, school, shopping or leisure trips). Significant shifts in stated preference are found for the car and bicycle modes. For example, 7 percent of the respondents preferred the car for commuting trips in 2014 and didn't in 2013. Also, 10 percent had a preference for cycling to and from work in 2014 but did not in 2013. We see similar changes for other trip purposes. To examine the influence of changing household interactions, we also took the impact of different life events that are measured in the MPN into account (Figure 2). A change in working hours, a new job and the birth of a child are the most frequent life events in the selected sample for the period 2012-2014. Some life events are very rare, such as 'household member passed away' and 'divorced / broke up'.

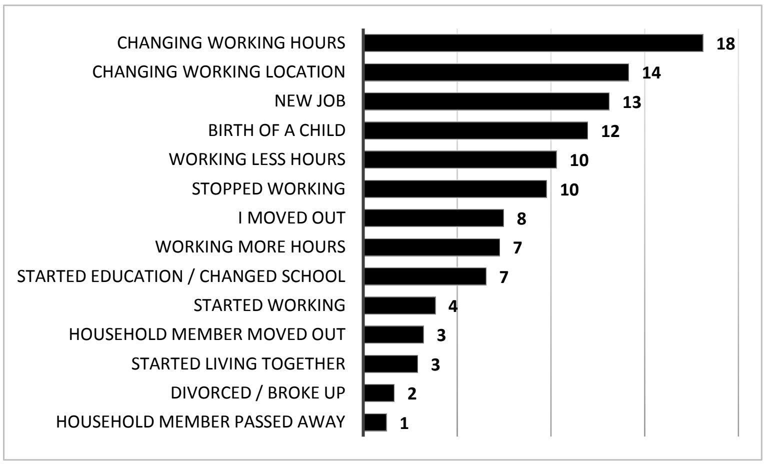

Figure 2. Frequency of life events (%) in the selected sample in the years 2012-2014

4. Results

Table 6 lists the estimation results. The random variables in the intercept-only model (M1) show that the intercept varies significantly across individuals as well as across households. The significant degree of variation among individuals and among households justifies the application of multilevel modelling (in this case, a three-level model). The intra-class correlation ρ for M1 shows that 23.4 percent of the variability of mode choice for home-based tours is between-household variation and 14.5 percent is between-person variation.

Next, we estimated a full model with both fixed and random effects (M2). By adding explanatory variables at each level (fixed effects), the variations between households and individuals on average (random 'intercept' effects) and among households in the impact of joint activity patterns on mode choice (random 'slope' effect) reveal some interesting results concerning household interactions. First, we see that joint tours were more frequently undertaken by car compared with individual tours. For partly joint tours with non-household members, car use is increased by about 57 percent and for fully joint tours with household members, the odds ratio of using the car is even about 4.2 times higher. For similar tours conducted in the previous year, car use was less likely. This probably means that cyclists show stronger habitual behaviour than car drivers and may suggest less involvement of household members. Two life events have a statistically significant impact on car use; both a change in working hours in 2012 and a change of work location in 2014 decreased car use. These results indicate a delayed effect of changing working hours on mode choice, whereas a change of work location immediately affects mode choice. Furthermore, individuals who stated a change in commuting mode preference towards the car for home-to-work trips were more likely to travel by car.

Variability among individuals accounts for 11.8 percent and variability among households accounts for 23.4 percent of the total variation in mode choice of home-based tours. Compared with the intercept-only model, random variation at individual level is slightly lower. This means that the explanatory variables capture part of the behavioural differences in mode choice. The random effects at household level show that the variation in mode choice among households occurs because on average (i.e. random intercept) and because the impact of joint activities on mode choice differs between households (i.e. random slope). The latter accounts for 13.0 percent of the total variation in mode choice. This finding indicates that interactions between household members, resulting in joint (or not) activity patterns, have significantly different outcomes for car use.

Because work and business tours have a higher share of car use, we expected that particularly dual-income households with one car need agreements on car use. Therefore, we estimated separate models for single-income and dual-income households. Most interestingly, the household random effect shows no significant effect for the intercept when only single-income and dual-income households are selected (M3). This indicates that for multiple-person households with single or dual incomes, the variability between individuals is much greater than the variability between households, and hence interactions between household members have a larger effect on mode choice. The variation between households in the effect of joint activity patterns on mode choice is still significant and accounts for 13.6 percent of the total variation. Shopping and personal services and preference for shopping trips have an insignificant coefficient in model M3, probably because single-income and dual-income households have less time for these activities compared with households without paid jobs (e.g., retired, unemployed). Partly joint tours with non-household members also have an insignificant coefficient in model M3. This confirms the finding that in single-income and dual-income households, interactions with household members have a larger effect on mode choice. The fixed effects for other types of joint tours are still significant, although the magnitude is smaller than in model M2.

The next model shows the fixed and random effects for dual-income households only (M4). In this model, the household level accounts for 17.2 percent and the individual level for 16.2 percent of the total variation in car use. Compared with model M3, dual-income households show more variation in mode choice between households than between individuals. This larger variation between households is fully explained, and is greater than in model M3 as a result of the random 'slope' effect of joint activity patterns. This indicates that in dual-income households, interactions between household members have a greater impact on car use. In addition, dual-income households show larger fixed effects for the accessibility of the destination. This means that accessibility determines the odds ratio of using the car for a home-based tour to a greater extent and suggests more household interactions. On the other hand, the magnitude of the fixed effects for joint tours is smaller in model M4 and only significant for fully joint tours with household members. This indicates less coordination between household members and is not according to a priori expectation, as we hypothesised that joint tours with household members would suggest stronger intra-household interactions. Repeating tours, life events and changing preferences show the same effect compared with model M3.

Table 6. Binary choice modelling results

		Multiple-person households							
		All hh		All hh		Single-income and dual income hh		Dual-income hh	
		M1		M2		M3		M4	
Parameters		Exp(B)	Sign.	Exp(B)	Sign.	Exp(B)	Sign.	Exp(B)	Sign.
Fixed part									
Intercept		1.016	0.822	0.123	0.000	0.107	0.000	0.130	0,010
Purpose tour	Social and leisure			0.442	0.000	0.412	0.000	0.341	0.000
(work=reference)	Shopping, personal			0.656	0.030	0.783	0.251	0.799	0.396
	Education			0.339	0.003	0.385	0.019	0.404	0.068
Distance tour				1.019	0.000	1.016	0.002	1.017	0.002
Joint activity (individual=reference)	Partly joint without hh			1.571	0.030	1.388	0.149	1.227	0.459
	Partly joint with hh			2.149	0.000	2.017	0.001	1.491	0.136
	Fully joint without hh			2.742	0.000	2.177	0.001	1.585	0.131
	Fully joint with hh			4.179	0.000	4.002	0.000	4.218	0,000
Accessibility	R-location			2.094	0.019	1.966	0.049	3.067	0.013
destination	D-location			1.648	0.103	1.527	0.203	2.372	0.047
(A-location=reference)	C-location			2.537	0.004	2.986	0.002	3.851	0.002
	B-location			2.283	0.006	2.191	0.019	3.368	0.004
PT season ticket				0.464	0.000	0.344	0.000	0.307	0.000
Car licence holder				7.050	0.000	9.867	0.000	7.181	0.000
Preference for cycling	Work trips			0.561	0.000	0.479	0.000	0.452	0.000
	Business trips			0.549	0.080	0.519	0.051	0.584	0.148
	Daily grocery trips			0.571	0.000	0.582	0.000	0.674	0.032
	Shopping trips			0.741	0.034	0.768	0.104	0.732	0.106
Always car available				2.935	0.000	2.509	0.000	2.375	0.000
Children <12 yr in hh				0.750	0.071	0.740	0.064	0.824	0.350
Income household	Single income			0.953	0.825				
(no income=reference)	Dual income			0.996	0.986	1.003	0.984		
Same tour in 2013				0.638	0.001	0.682	0.009	0.619	0.008
Same tour in 2014				0.814	0.093	0.824	0.157	0.805	0.203
Changing	In 2014			1.070	0.755	1.134	0.581	0.786	0.366
working hours	In 2013			0.842	0.444	0.862	0.520	0.704	0.149
	In 2012			0.379	0.012	0.383	0.017	0.304	0.005
Changing	In 2014			0.559	0.017	0.581	0.031	0.585	0.053
work location	In 2013			1.258	0.394	1.253	0.401	1.589	0.118
	In 2012			0.766	0.623	0.755	0.603	0.994	0.992
Changing preference car	For work trips			2.000	0.019	2.175	0.009	1.767	0.103
Random part									
Level 1 – between tours		1.000		1.000		1.000		1.000	
Level 2 – between indiv.		0.765	0.000	0.598	0.001	0.937	0.000	0.798	0.004
Level 3 – between hh		1.239	0.000	0.524	0.008	0.159	0.453	0.029	0.903
Level 3 – joint activity				0.662	0.000	0.667	0.001	0.849	0.002
N (tours)		*3266*		*3266*		*2.496*		*1.575*	
ρ (level 2)		14.5%		11.8%		19.1%		16.2%	
ρ (level 3)		23.4%		23.4%		13.6%		17.2%	
Correctly predicted		83.2%		87.8%		87.5%		87.3%	

5. Conclusions and future research

The main objective of this study was to explore the influence of household interactions on car use for home-based tours, using data from the first two waves of the MPN. We estimated multilevel binary logit models to investigate to what extent relations between household members affect car use. We created a set of explanatory variables for three different levels, namely the household, individual and tour level. These variables were used to explain variation in car use between and within these levels (i.e. random effects and fixed effects). We added repeating tours in the same and previous year and life events to the model to analyse the impact of changes in household and individual characteristics over time on car use.

The results show that variation in mode choice can be explained by variability between household and individuals and justifies a multilevel modelling approach. Variability between households and individuals accounts for about one third of the total variation in mode choice of home-based tours. The first important conclusion is, therefore, that multilevel analysis is able to add knowledge about intra- and inter-household variation in car use. Joint tours are more frequently undertaken by car than individual tours and the impact of joint activities on mode choice differs between households. This finding indicates that interactions between household members, resulting in joint (or not) activity patterns, have significant different outcomes in terms of car use. For dual-income households only, the variability between individuals is greater than the variability between households. This indicates that intra-household interactions have a greater effect on car use in dual-income households, probably because there are more aspects to consider that impact car use (for example, having two work locations instead of one, with different accessibility types). Different explanatory variables show a significant impact of household interactions on car use. Firstly, fully joint tours form the strongest predictor in a given situation: if somebody travels together with a household member, he or she is much more likely to use the car. The purpose of a trip is another significant predictor. Work and business tours have a higher likelihood of car use. This is confirmed at the individual level, where fulltime workers are more likely to use the car. This implies that in the case of two or more employees in a one-car-household, decisions have to be made about who gets to use the car. Furthermore, the results indicate a delayed effect of changing working hours on mode choice, whereas a change of work location immediately affects mode choice.

The results provide us with a better understanding of intra- and inter-household interactions and their impact on car use. Policy makers should take into consideration that in multi-person and specifically in dual-income households, car use is more strongly affected by relationships between household members. For example, encouraging specific types of commute mode change is not just about commuting distance at the individual level. Decisions on car use also depend on agreements about who will take the children to school before going to work, who will do the groceries after work or commuting distance of the spouse.

There are several directions for future research. A first direction is to widen the scope of the analysis. For example, the models can be expanded with interaction effects, mode choice alternatives, and other random 'slope' effects or can be evaluated for different distance classes. Another worthwhile extension of the analysis could be to include explanatory variables representing features of one or more household members, such as commuting distance of the spouse or parallel activities. As stated before, it would also be interesting to focus on home-based work tours, to determine if other variables such as ICT use are significant. Finally, analysing more dimensions than only mode choice, for example tour distance, travel time and activity duration, would be a challenging and interesting task for future research. A second direction for future research is to examine the dynamics in household interactions over a longer time period and the influence of these changes on mode choice behaviour. It is intriguing that we found already significant temporal effects when analysing only two waves; once data for subsequent years become available, more sophisticated panel analyses can be conducted. Within the multilevel approach, this means that repeated measures nested within individuals can be added to the model specification. Van Acker and Witlox (2010) raised the question whether car availability is just a predictor of car use or a result of a decision-making process itself. Exploring this kind of causal relations in both research directions using panel data is a third interesting research topic for the future.

References

Anggraini, R., Arentze, T., and Timmermans, H. (2008). Car Allocation between Household Heads in Car Deficient Households: A Decision Model. European Journal of Transport and Infrastructure Research, 301-319.

Bhat, C.R. and Pendyala, R.M. (2005). Modeling intra-household interactions and group-decision making. Transportation, 32, 443-448.

Bamberg, S. I. P. (2003). Choice of Travel Mode in the Theory of Planned Behavior: The Roles of Past Behavior, Habit, and Reasoned Action. Basic & Applied Social Psychology, 25(3), 175.

Borgoni, R., Ewert, U.C. and Fürnkranz-Prskawetz, A. (2002). How important are household demographic characteristics to explain private car use patterns? A multilevel approach to Austrian data. MPIDR Working Paper WP 2002-006, February.

Bullen, N., Jones, K. and Duncan, C. (1997). Modelling complexity: Analysing between-individual and between place variation – A multilevel tutorial. Environment Planning A 29: 585-609.

Cherci, E. and Cirillo, C. (2008). A modal mixed logit choice model on panel data: accounting for systematic and random heterogeneity in preferences and tastes. 86th Seminar on Transportation Research Board. Washington DC, USA.

Cherci, E. and Cirillo, C. (2014). Understanding variability, habit and the effect of long period activity plan in modal choices: a day to day, week to week analysis on panel data. Transportation, 41, 1245-1262.

Chlond, B. and Lipps, O. (2000). Multimodalität im Personenverkehr im intrapersonellen Längschnitt. In: Stads Region Land, Institut für Stadtbauwesen der RWTH Aachen, Band 69. Aachen, Germany.

Ettema, D., Schwanen, T., and Timmermans, H. (2007). The effect of location, mobility and socio-demographic factors on task and time allocation of households. Transportation, 89-105.

Gliebe, J. P., and Koppelman, F.S. (2005). Modeling household activity-travel interactions as parallel constrained choices. Transportation, 32(5), 449-471.

Goulias, K.G. (2000). Repeated measures multilevel analysis of daily time allocation to activities and travel. Citrans Working Paper, March.

Hedeker, D. (2007). Multilevel Models for ordinal and nominal variables. In J. de Leeuw and E. Meijers (Eds.), Handbook of Multilevel Analysis (pp. 341-376). Springer, New York, NY, USA.

Hilbers, H., Snellen, D. and Hendriks, A. (2005). De invloed van de werklocatie. NAI Uitgevers / Ruimtelijk Planbureau, Rotterdam/The Hague, the Netherlands.

Ho, C., C. Mulley (2015a), Intra-household interactions in transport research: a review. Transport Reviews, 35(1), 33-55.

Ho, C., C. Mulley (2015b), Intra-household Interactions in tour-based mode choice: The role of social, temporal, spatial and resource constraints. Transport Policy, 38, 52-63.

Ho, C., and Mulley, C. (2013). Tour-based mode choice of joint household travel patterns on weekend and weekday. Transportation, 40(4), 789-811.

Hoogendoorn-Lanser, S., Schaap, T. W. and Olde Kalter, M.J.T. (2015). The Netherlands Mobility Panel: An innovative design approach for web-based longitudinal travel data collection. Transportation Research Procedia, 11, 311-329.

Hox, J. (2002). Multilevel analysis: Techniques and applications. Lawrence Erblaum Associates, Mahwah, NJ, USA.

Hox, J. (2010). Multilevel analysis: Techniques and applications (2nd ed.). Routledge, New York, NY, USA.

Kloas, J., and Kunert, U. (1994). Über die Schwierigkeit, Verkehrsverhalten zu messen. Die drei KONTIV-Erhebungen im Vergleich. In: Verkehr und Technik, Heft 3 und 5. Firmware Entwicklung, Lumino GmbH. Krefeld, Germany.

Klockner, C.A. Friedrichsmeier, T. (2011). A multilevel approach to travel mode choice – How person characteristics and situation specific aspects determine car use in a student sample. Transportation Research Part F: Traffic Psychology and Behaviour, 14(4), 261-277.

Kreft, I. and De Leeuw, J. (1998). Introducing multilevel modeling. Thousand Oaks, CA: Sage.

Lipps, O., and Kunert, U. (2005). Measuring and Explaining the Increase of Travel Distance: a Multilevel Analysis Using Repeated Cross Sectional Travel Surveys.

Liu, X. (2016). Methods and Applications of Longitudinal Data Analysis. Academic Press, Oxford, UK.

Maat, K. and Timmermans, H. (2009). Influence of residential and work environment on car use in dual-earner households. Transportation Research Part A: Policy and Practice, 43(7), 654-664.

Miller, E. J., M. J. Roorda, J. A. Carrasco (2005., A tour-based model of travel mode choice. Transportation, 32(4), 399-422.

Olde Kalter, M.J.T., Geurs, K.T., Hoogendoorn-Lanser, S. and Beek, van P. (2014) Mode-choice behaviour for home-based work trips: The first results of the new Netherlands Mobility Panel. Paper presented at 10th International Conference on Survey Methods in Transport, 16-21th November 2014, Leura, Australia.

Schwanen, T., Dieleman, F. M., and Dijst, M. (2004). The Impact of Metropolitan Structure on Commute Behavior in the Netherlands: A Multilevel Approach. Growth & Change, 35(3), 304-333.

Schwanen, T., Ettema, D. and Timmersmans, H. (2007). If you pick up the children, I'll do the groceries: spatial differences in between-partner interactions in out-of-home household activities. Environment and Planning A, 39(11), 2754-2773.

Stopher, P.R., Hartgen, D.T., and Li, Y. (1996). Smart: Simulation model for activities, resources and travel. Transportation 23, 293-312.

Timmermans, H. (2009). Household Decision Making in Travel Behaviour Analysis. In The Expanding Sphere of Travel Behaviour Research (pp. 159-185). Emerald Group Publishing, Bingley, UK.

Timmermans, H. J. P., and Zhang, J. (2009). Modeling household activity travel behavior: Examples of state of the art modeling approaches and research agenda. Transportation Research Part B: Methodological, 43(2), 187-190.

Van Acker, V. and Witlox, F. (2010). Car ownership as a mediating variable in car travel behavior research using a structural equation modelling approach to identify its dual relationships. Journal of Transport Geography, 18, 65-74.

Vovsha, P., Petersen, E., and Donnelly, R. (2007). Explicit modeling of joint travel by household members: statistical evidence and applied approach. Transportation Research Record, 1-10.

Vovsha, P. and Petersen, E. (2005). Escorting children to school: Statistical analysis and applied modeling approach. Transportation Research Record: Journal of Transportation Research Board, 1921, 131-140.

Wang, D. and Li, J. (2009). A model of household time allocation taking into consideration of hiring domestic helpers. Transportation Research Part B: Methodological, 43, 204-216.

Yang, D., and Timmermans, H.J.P. (2015). Analysis of consumer response to fuel price fluctuations applying sample selection model to GPS panel data: Dynamics in individuals' car use. Transportation Research Part D: Transport and Environment, 38, 67-79.

Yarlagadda, A. and Srinivasan, S. (2008). Modeling children's school travel mode and parential escort decisions. Transportation, 35, 201-218.