THE DETERMINANTS OF MODE CHOICE FOR FAMILY VISITS – EVIDENCE FROM DUTCH PANEL DATA

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ABSTRACT

Family members are central in people's social networks and traveling to maintain face-to-face contact with them takes up a substantial share of total travel. We focus on how the need for family visits and their context affect travel mode choice for those visits. We make use of the LISS panel data to estimate multinomial logit regressions for the effect of individual characteristics, distance between family members, household composition and degree of urbanization on mode choice for family visits in the Netherlands. We propose a variation of the Mundlak specification for panel data, which improves the handling of unobserved heterogeneity in preferences regarding residential location and travel modes, a central yet rarely addressed problem in mode choice research. With our approach we are able to differentiate between individual effects and between-group effects and to estimate both time-constant and time-varying variables. With respect to household size and composition, we find that living with a partner, having at least one child and having a child under 6 years of age, all affect negatively the likelihood of using public transport for family visits. Walking and cycling is mainly associated with distance of travel: the shorter the distance the higher the likelihood of using slow modes instead of a car. Those living in higher residential densities have a higher likelihood of using public transport relative to using cars and to those living in lower density areas. Density at the trip-origin has no significant association with traveling by walking or cycling, while at the destination it is negatively correlated with the use of slow modes.

Keywords: family visits, mode choice, travel behaviour, panel data, the Netherlands

INTRODUCTION

Face-to-face contact between family members serves multiple purposes. It reinforces feelings of affection (Lawton et al., 1994) and it is helpful in developing solidarity within the family sphere (Brownstone, 2008). For example, by visiting elderly parents, grown up children provide a major source of instrumental and emotional support (Smith, 1998). Family visits can also facilitate exchange of both goods and services that are necessary for the individual's well-being (Komter & Vollebergh, 2002).

Statistics show that indeed people invest time and effort into visiting other family members by traveling: in 2010, 12% of all journeys in the Netherlands were categorized under visiting friends and family", compared with home-work journeys that made up 18% of all journeys. In terms of distance, visiting family and friends comprised 16% of distance travelled (CBS, 2010). Previous research has found the category visiting family and friends to have the highest share of total leisure trips (Schlich et al., 2004). With the growing role leisure activities play in modern life non-work related travel started receiving growing attention by scholars (Schlich et al., 2004; Ettema & Schwanen, 2012). However, only little attention has been paid to the specificities of visiting family (and friends). We bridge this gap by focusing specifically on family visits as an important part of non-work travel.

Traveling for meeting family shares some commonalities with other types of leisure travel. For example they both take a more flexible form in terms of schedule than travel for work. Visits may take place during week days but also often on the weekends. However, family visits differ from leisure activities in several important features: previously it has been claimed that leisure travel is less affected by necessities and is lacking temporal or spatial fix (Ohnmacht et al., 2009) but for family visits the location of the activity is often constrained to the household of a family member. One has a choice of many tennis clubs or amusement parks but attending dinner at one's parents' home is spatially constrained. Second, while frequency of visits may vary, social norms can create a lower bound for number of visits. That is, people may feel obliged to conduct a visit, limiting the voluntary dimension of this travel (Stein et al., 1998). The latter also distinguishes family ties from friendships for which geographical barriers, such as distance may lead to discontinuation of contact, while this is not the case with family. Third, family visits are often a coordinated activity that involves other members of the household (Farber & Paez, 2011), as is the case when parents take their children to meet their grandparents. The three constraints we suggest above make family visits a more nuanced type of leisure travel and thus call for a separate analysis.

As stated above, physical travel enables face-to-face meetings that contain benefits for the individual and for the family, but on the other hand travel is costly, both in monetary terms and in terms of time spent traveling. Individuals therefore make trade-offs between travel and other alternatives, such as residential mobility (moving closer to family members), or replacing visits by phone or internet contact, though the latter is not necessarily (only) a substitute (van den Berg, Arentze, & Timmermans, 2010). Individuals can mitigate the costs attached to traveling for visiting purposes by deciding for example on the appropriate frequency and duration of visits (how often to travel and for how long) and by choosing mode of travel (by what means to travel).

In this paper we focus on the determinants of mode choice: what factors have an effect on travel mode choice for family visits in the Netherlands. We have chosen to focus on mode choice as this decision affects not only the individual but it potentially contains substantial external costs for society. Travel creates traffic congestion, pollution and noise, and infrastructure takes up large amounts of space. These negative effects are strongly associated with the amount of mobility performed by car (Bertolini & Le Clercq, 2003; Banister, 2005). High car usage is also hypothesized to be disadvantageous for social relations (Putnam, 2000; Urry, 2007). In the Netherlands in 2010 57% of journeys for social reasons were made by car compared with 36% by cycling or walking and 3% by public transport (CBS, 2010). Understanding the socio-economic and spatial features of these journeys is crucial in developing sustainable alternatives. In this research we exploit a unique panel data survey designed especially for this purpose. The three-wave panel data cover in detail some 1,500 individuals living in the Netherlands. The data at our disposal allow us to deploy advanced panel data regression analysis, which includes different sets of socio-economic and spatial variables, and test to what extent they explain mode choice for family visits in the Netherlands.

THEORETICAL FRAMEWORK

Visiting other members of family is an activity that is undertaken for several reasons. We understand the act of visiting kin as part of what Rossi and Rossi (1990) call “the kinship system” and as a manifestation of multiple dimensions of intra-familial solidarity. In the typology of intergenerational solidarity suggested by Bengston and Roberts (1991), parent-child visits are part of several dimensions of solidarity they identify. They see a visit as part of functional solidarity – the degree of exchange of assistance in the family, and also as an aspect of associational solidarity – the amount of shared time family members spend with each other.

Obligations towards kin are also an essential part in family relationships and in face-to-face visits, although their level may vary by gender, with women experiencing greater felt obligation (Stein et al., 1998), or by beliefs on family duties (Killian & Ganong, 2002). According to Rossi and Rossi (1990), children paying a visit to their parents are following a cultural-normative obligation, determined by the understanding of what is expected of them. In parallel, they are acting in a concrete network of kinship ties. The functioning of the network is determined by the geography (how far family members live away), the economics (what resources are shared) and the history of the specific network (past family events). Mancini and Maxwell (1990), looking at sibling relationships, claimed that these could be based on obligatory motivations, such as feeling of responsibility towards one’s kin, but also on more discretionary motivations, such as admiration and common interest. Given the obligations, solidarity and expectations from one another within the family network, and given the distance between family members, traveling for the purpose of visiting a family member is a necessary tool to bridge the geographical distance between family members.

The household decision on mode choice for conducting a visit is not disconnected from the background of the visit as we described above. Different mode choices offer different opportunities directly related to the circumstances of the visit. Based on the conceptualization above and on existing travel behaviour research (e.g. Dieleman et al. 2002, Limtanakool et al., 2006, Cervero, 2002; Schwanen et al., 2004; Van Acker et al., 2008) we can identify factors that may influence mode choice for traveling for visiting purposes. We group these factors into: spatial characteristics of the trip – distance and degree of urbanization at origin and destination; household characteristics – size and age composition of household members, especially number and age of children; socio-economic status – education and employment situation; individual residential background – type of urban environment at the place of residence at age 15.

It has been argued that mobility by car offers access to more geographically disparate activities than other modes (Schönfelder & Axhausen, 2003; Sheller & Urry, 2003; Farber & Páez, 2009; Schwanen & Lucas, 2011). As with leisure activities in general, the car is especially useful when an activity, which does not necessarily happen on a daily or even a weekly basis, needs to be woven into the family schedule of work, school and maintenance activities. Therefore family visits may require high flexibility and may lead to intensive car use, especially where distances are substantial. In cases where travel distances are short, slow modes such as walking or cycling may provide the necessary flexibility as these modes do not require fixed schedules. Our first hypothesis (1) is thus: long distance travel to family members is associated with more car use; for short distances – with more slow mode use.

Apart from travel distance, also involvement of other household members in visits may play a role. Travel behaviour studies have argued before that household composition affects mode choice and other aspects of travel. Dargay and Hanly (2004) found that single adults are more likely to use public transport and walk compared with couples. The presence of children in the household appeared to be associated with more car use and less public transport use. For leisure trips Dieleman et al. (2002) found that households with children in which both adults work travel shorter distances with all modes, compared to childless couples. Similar results were found by Ohnmacht et al. (2009) who also found smaller share of bicycle-use in larger households. Partly contradicting these findings, Limtanakool et al. (2006) found that specifically in long distance leisure trips families with children travel more by train than single households.

For household size and composition, several effects are plausible: the bigger the household size, the more people who may join visits to an out-of-household family member, thus making traveling by public transport relatively more expensive. In addition, from a coordination perspective, a bigger household might find it more difficult to conduct visits with all members attending, which may require higher flexibility in scheduling. Finally, household size may lead to an indirect time budget effect. The larger the number of children the more time is allocated to routine household tasks and childcare and more effort is being put into trip chaining (Van Acker et al., 2008; Heinen et al., 2010). Car travel is associated with higher flexibility and with decreasing marginal costs per traveller, and thus these effects lead to our hypothesis regarding household size in hypothesis 2: Bigger households will be associated with more car travel and less use of public transport. The effect on slow modes is ambiguous.

Next to household size, we also consider the age distribution of its members. Making use of a life-cycle perspective and data from Edinburgh Ryley (2006) found that families with young children are more car-dependent than other families. Zwerts et al. (2007) found evidence that parents of young children make more trips than other couples. At an early age children may not be able to walk or cycle a long distance and for the parents the use of public transport in combination with young children may be cumbersome. Perceptions of car travel as safer than its alternatives could also affect the decision. We hypothesise (hypothesis 3) that having young children is associated with more car travel relative to both alternative modes.

Beyond variables directly relating to family relationships and the household we follow the travel behaviour literature and consider the residential areas of the different family members in terms of their spatial characteristics. While the direction of causality between land use structure and travel behaviour is hotly debated (see: Naess, 2006 and a review by Cao et al., 2009), some outcomes are consistently found in the literature. Higher built area densities are associated with higher levels of walking, cycling and use of public transport (Cervero, 2002; Schwanen et al., 2004; Van Acker et al., 2008). Similar results were found when considering land use diversity – the degree of activity diversity in a given area (Cervero & Kockelman, 1997) – areas characterised with high diversity are also characterized by high use of public transport, high levels of walking and lower levels of car use of their residents. Also research on leisure travel found results along these lines: In Switzerland Ohnmacht et al. (2009) found that residents of city centres have lower car share for leisure trips. In the Netherlands Limtanakool et al. (2006) found significant negative correlations between living in a suburb or in areas with low degree of urbanization and the likelihood of traveling by train on long distance leisure trips. Following previous work by Cervero (2002) and Limtanakool et al (2006), in the empirical analysis we will consider the spatial characteristics at both the origin of the trip and at the destination. The hypothesis for both origin and destination follows the same expectation (hypothesis 4): living in more urban areas is associated with more public transport use and with less car use.

DATA AND METHODS

The data

This study is the first to use the Mobility in Social Networks module of the LISS panel1, a 3-wave panel covering the period 2009-2011, as the main data set. The data were collected through an internet based survey among a random sample of Dutch speaking, aged 16 and above, residents of the Netherlands. For the first wave, out of the 8,093 panel members that were approached, 5,143 of them fully completed the questionnaire, 4,128 fully completed the second wave and 3,518 fully completed the third wave. Assuming there was no systematic attrition, we selected only those individuals who completed all three waves of the questionnaire. Furthermore, in order to avoid issues associated with ageing, such as deterioration of driving abilities and death of siblings, or with students who for example enjoy in the Netherlands free usage of public transport, we selected those individuals belonging to the main working age population: between the ages of 25 and 60. Finally, we kept those individuals who did not have missing information on the main variables as detailed below. The final sample used for our all regression models consists of 1,582 persons. In the data used for this paper there is an over-representation of females and under-representation of migrants and residents of the largest cities.
These panel data uniquely combines detailed geographic information about the residential location of the respondents and of their family members, as well as information on their travel behaviour and interaction patterns within the family network. For the purpose of this paper we used the following variables from the dataset: first, basic individual characteristics -

[1] The LISS panel is collected by CentERdata – http://www.centerdata.nl

gender, age, education level and work status of the respondent, of which the latter two proxy socio-economic status. Education level was measured in three levels: low (completed primary school or intermediate secondary school), medium (completed higher secondary education or intermediate vocational education) and high (completed high vocational education or university). Secondly, to account for household size five variables were used. One dummy variable measures whether the respondent lived with a partner, one dummy variable measures if there is a child younger than 6 in the household and then three dummy variables represent the number of children under the age of 18: at least one, at least two and at least three children. This structure for number of children was used in order to facilitate the regression model used as explained below. Residential history was recorded as "type of urban environment at age 15". This was measured in three categories: the 22 core cities as defined by Statistics Netherlands, their adjacent suburban municipalities, and other places, representing small towns and rural areas.

Every individual reported their current location of residence at a four-digit postcode precision. For all subsequent analysis we assume the individual lives in the geometric centre of the postcode area. We joined this piece of data with the Statistics Netherlands (CBS) database of the geographic characteristics of the postcode area and calculated three variables that indicate the characteristics of the postcode in terms of urbanization. First, degree of urbanization of the area measured in three categories: high (more than 1500 address per km2), medium (500-1500 addresses per km2) and low (less than 500 address per km2). Second, the average car ownership per household in the postcode in two categories: high (more than 1 car per person) and low (1 car or less per person). Third, average household size in the area in three categories: high (more than 2.5 persons per household), medium (2-2.5 persons per household) and low (less than 2 persons per household). All these variables represent different dimensions of the type of each residential area, where the more urban areas have of high address density, low average household size and low average of car ownership per household, while the less urban areas have low address density, medium or high average household size, and high average car ownership. Every respondent was asked to report the postcode area of residence for out of household first degree family members: parents, up to 3 children and up to 3 siblings. These data were also combined with the CBS data as explained above. In total, the dataset is a collection of ego-centric visit networks, where each first degree family relationship (ego-parent, ego-sibling and ego-child) is a dyad. For each of these relationship dyads the respondents reported the annual frequency (in seven categories) of their visits and which mode of travel usually used for these visits.

Finally, a distance matrix provided by Goudappel Coffeng2, a private consultancy firm, enabled us to calculate exact road distance between every pair of postcodes, thus giving us the distance between the respondent and every first degree family member. We chose explicitly for road distance as this represents the baseline distance of travel when an individual considers visiting a family member.

In the final dataset each data-point represents a dyadic relationship: the background variables of the ego, the distance to the alter, geographic attributes of their respective locations and the mode used by the ego to visit the alter. Due to sample size limitations in the researched age group we made use of the data of two types of relationships: child-parent

[2] The data are taken from The National Accessibility Map (Nationale Bereikbaarheidskaart) produced by Goudappel Coffeng- http://www.bereikbaarheidskaart.nl/

and siblings. We split the dataset along types these two dyadic relationships: ego-parent and ego-sibling. Individuals may appear several times in one subset. For example persons with two out-of-home siblings would appear twice the ego-sibling subset.

Methodology

After presenting basic descriptive statistics of the sample, we focus on mode choice decisions in a multinomial logistic regression, where given the above mentioned variables the individual faces a choice between three modes of travel: car (the base category), slow modes (which include walking and cycling) and public transport (which include train, bus and tram). Our data do not allow us to distinguish between driving a car and riding as a passenger.

The baseline model we estimate is the following:

$$\ln\frac{P(mode_{ijt})}{P(car)} = x_{it}'\beta + dist_{it}'\gamma + urban_{it}'\delta_1 + urban_{jt}'\delta_2 + c_i + \varepsilon_{it} \quad (1)$$

For every individual i visiting family member j at period t, mode choice (slow mode or public transport) is dependent on all individual-level variables (x), travel distance between the individual and the family member, urban environment of the individual and of the relative, and a composite random term of both time specific and individual specific errors which is allowed to be correlated between observations of individual i. In our model we also assume variable c_i which represents a time-constant individual specific effect to account for unobserved heterogeneity. All coefficients of the model are measured as relative to the baseline mode – car travel.

In panel data models such as ours, two issues are of central concern: the first is the assumption that observed independent variables are strictly exogenous and the second issue revolves around the question of whether the unobserved individual effect is uncorrelated with other independent variables.

Strict exogeneity is defined as:

$$E(\varepsilon \mid X) = 0 \quad (2)$$

It demands that the error terms are uncorrelated with past, current and future terms of every independent variable. This assumption could be violated if for example the distance between a person and their family member is not independent of the person's previous mode choice decisions. If the regression model violates the strict exogeneity assumption it may have severe consequences: it may lead to inconsistent estimates. The remedy for this concern, using Instrumental Variables (Halaby, 2004), was not available to us. In the scope of this paper we cautiously assume that since visiting family members is not a daily activity such as commuting, it only has a second-order effect on the decision where to reside, and hence on distance travelled. To be sure, we refrain from interpreting the effect of distance on mode choice as causal and present the relevant results strictly as correlations.

The second cause for concern we need to examine is the potential correlation between the unobserved individual effect (c) and other independent variables (X) (see: Mokhtarian & Cao, 2008). An example of such correlation is when individual characteristics and place of residence are correlated with unobserved preference for a mode of travel. A person who has strong preference for cycling might choose to live in an area with ample cycling opportunities (e.g. available cycling paths and desired amenities within cycling distance). Neglecting this correlation would lead to biased estimates.

A straightforward way to reduce this correlation is to add variables that emulate the unobserved ones. In the case of mode choice we would like to especially proxy the idiosyncratic preference for a specific travel mode. We argue that these preferences were partly shaped through the experience of growing up in a certain built environment, which, as we discussed above, usually correlates with certain means of travel. Ideally we would have liked to be able to control for the history of mobility patterns of the individual (i.e. the mode of travel used in childhood). Unfortunately with the data at hand we cannot do so, but we can observe residential experience: in what type of residential environment individuals spent their youth. Research has shown that past residential experience has an effect on current residential choices. Feijten et al. (2008) found that growing up in rural and suburban regions in the Netherlands leads to preferring these types of residential environments. Blaauboer (2011) found that persons who lived in urban and suburban areas at the age 15 had a higher likelihood to move to similar areas when they were adults. If residential experience appears to partially explain current preferences then we might be able to extrapolate these findings to travel behaviour. Individuals who lived in urban environment at the age of 15 were possibly more likely to travel by public transport than those who grew up in suburban and rural areas. We expect that this behaviour from earlier ages may partially explain current travel behaviour and thus these persons would also as adults use the car less often. Those who grew up in rural or suburban areas would exhibit the opposite behaviour. As mentioned above, in our models we included the variable "type of urban environment at age 15" in three categories: urban, suburban and rural.

An alternative method to account for unobserved heterogeneity, which is often preferred in panel data studies, is the Fixed Effect estimation (Wooldridge, 2002; Halaby, 2004). In this procedure variations between units are removed and only the variation within the unit is taken into consideration, thus "problematic" time-constant unobservables are removed. However, the downside is that also the effect of time-constant observed variables, such as gender or completed education, cannot be estimated. As these variables are at the heart of our analysis we are required to find a procedure which both accounts for the afore-mentioned correlation and keeps all variables of interest as part of the regression.

One possible solution is to adopt the model suggested by Mundlak (1978). Mundlak suggested adding the individual mean of time-varying variables as regressors to the model as follows:

$$\ln \frac{P(mode_{ijt})}{P(car)} = x_i'\beta + z_{it}'\lambda + \overline{z_i}'\theta + \varepsilon_{it} \qquad (3)$$

In equation 3 x is a vector of time-constant individual-level variables, and therefore the subscript t is removed. z is a vector of variables that may vary between the panel waves, such as age, household size and travel distance and $\overline{z_i}$ is a vector of the within-individual means. The vector of means absorbs the correlation between the unobserved time-constant characteristics and the z type (time-varying) variables. The requirement from the model is subsequently reduced to making sure that the unobserved characteristics are uncorrelated with the time-constant variables only – a weaker assumption. Thus Mundlak's specification indeed accounts for unobserved heterogeneity and for the correlation with independent variables, while still allowing for the estimation of the effect of time-constant variables.

The disadvantage of the Mundlak method is that coefficients of the mean-vector are usually left without a useful interpretation. Therefore we follow Bartels (2008) and Bell and Jones (2012) who proposed a Mundlak-type formulation which explicitly includes two effects: a within-individual effect and a between-individual effect. This formulation is identical to Mundlak's original expression except that theirs replaces time-varying variables with their demeaned version:

$$\ln\frac{P(mode_{ijt})}{P(car)} = x_i'\beta + (z_{it} - \overline{z_i})'\lambda + \overline{z_i}'\theta + \varepsilon_{it} \qquad (4)$$

By demeaning the z-type variables, any collinearity between them and the vector of means is removed and the coefficients could be interpreted as a "within-effect" (λ) and a "between-effect" (θ).

We estimated equation 4 for two types of family relationships: a child visiting a parent and siblings visiting each other. We refer to equation 4 as the "within-between" model. We refer to the pooled-data regression of equation 1 as the baseline model for our results. In both the baseline and the within-between models standard errors were clustered by individual to incorporate the serial correlation between observations of the same individual and across time.

DESCRIPTIVE STATISTICS

Table 1 shows that a simple comparison between persons visiting their parents and visiting their siblings confirms what has already been identified in the literature that on average persons live closer to their parents than to their siblings (Mulder & Kalmijn, 2006) – in the sample children live, on average, 32 kilometers away from their parents while 41 kilometers from their siblings. In general the two dyadic relationships differ by modal split. In Table 1 we further find that respondents report car travel more often when visiting siblings than when visiting parents.

Inspecting each type of visit separately in Table 2 we find above average car use for family visits by men, by highly educated individuals, by couples, by parents of children, by parents of children under the age of 6 and by individuals with a job. We note an especially high frequency of visiting family using slow modes by less educated respondents. Although public transport use is much lower compared with other modes of travel, it is above average among highly educated, single, and people without children in the household. With respect to type of urban environment at age 15, it is apparent that the categories differ by their use of public transport: those who grew up in the 22 core cities make above-average use of public transport for family visits.

The degree of urbanization at origin and destination are not equally distributed in our sample: For siblings the distribution of trip origin and destination is similar, with most trips originating and terminating in rural areas (39%). For the child-parent dyads the most common origin is in suburban areas (35.6%) and the most common destination is in rural areas (38.7%). The other two postcode level variables (average household size and average car ownership) display similar distribution of frequencies as the level of urbanity: the most common origins and destinations are in areas of medium and high household size and with high car ownership rates, both typical for suburban and rural areas. Modal split in origin areas is tilted towards cars in areas of medium density, high average household size and, as expected, in areas of high average car ownership. Car use seems to fluctuate less by destination area urbanity. Only in rural areas (areas of low address density) car use is slightly higher than average (74.4% compared with an average of 71%, for the child-parent dyads).

MULTINOMIAL REGRESSION RESULTS

We present the results of the regressions for the baseline (pooled) model (equation 1) and the within-between model for the child-parent dyads and for the sibling dyads, one with the geographical variables and one without – in total eight regressions. The results are presented in Table 3; models 1 through 4 are the results for children visiting parents and models 5 through 8 the results for sibling-visits.

Model performance

Three criteria are used to assess model performance: the log-likelihood test, Akaike's Information Criterion (AIC) and Bayes Information Criterion (BIC). We find that only in one case, and only by using the log-likelihood test the within-between specification out-performed the baseline model: model 6 is significantly better than model 5 (p=0.03). This is not surprising since with the within-between specification, degrees of freedom are traded off for an improved specification of unobserved heterogeneity and for added insight on how the variance is split between the two types of effects (Bell & Jones, 2012) – by no means a trivial benefit. With a longer panel and more variations between the waves we expect this trade-off to have even greater benefits.

Time-constant variables

In all models there are three time-constant variables: gender, education levels and type of urban environment at age 15. From the child-parent models we learn that all-else equal, women have positive log-odds compared with men for choosing walking and cycling over using the car. Regarding education, we see in models 1 through 4 that lower educated persons are less likely to use slow-modes compared to those with medium and high levels of education. This relationship remains intact even after controlling for current place of residence and trip destination. At the same time, models 5 and 6 show that highly educated persons are more likely to use public transport rather than cars compared with those with medium and low level education. Previous research have shown that distances between family members are larger for highly educated (in the US: Rogerson et al., 1993; in the Netherlands: Kalmijn, 2006) and that highly educated persons travel longer distances for

leisure activities (Dieleman et al., 2002). But in contrast to our findings here regarding family visits, for general leisure travel Dieleman et al. found that highly educated people are more likely to travel by car. This may suggest that traveling for family visits indeed presents a different case of travel behaviour than other forms of leisure travel, which have more diffused destinations. Our findings that highly educated are more likely to travel by public transport is in line with the findings that in the Netherlands the highly educated tend to concentrate in the largest cities (Feijten et al., 2008; CBS, 2010), where the public transport system is more developed. We find additional evidence for this in models 7 and 8, where adding controls for location of origin and destination indeed turns the effect of education levels insignificant.
For the variable "type of urban environment at age 15", somewhat surprisingly, persons growing up in the largest cities compared with those growing up in rural area, have a lower likelihood of using slow modes relative to cars (models 1-4). In line with expectations, models 5 and 6 show that growing up in cities contributes to more use of public transport. In all models there was no significant difference was found between mode choice of those living at age 15 in suburban areas and in rural areas.

Time-varying variables

In the eight regressions there are six central time-varying variables: age, number of children, a dummy variable representing a child younger than 6, a dummy for living with a partner or not, a dummy for having a job or not and distance to family relative in kilometres.
All models but one (model 8) predict that age is negatively correlated with public transport use – all else equal, older individuals have a higher likelihood of choosing car over public transport. With respect to slow modes, model 4 reveals that while there is no significant difference between older and younger respondents (the "between" effect), as individuals grow older the likelihood of them to choose slow modes over cars is decreasing (a negative log-odds in the "within" effect). A similar example for the importance of separating within and between-effects is the job-status variable. Models 6 and 8 show that with respect to the likelihood to choose slow modes over cars, respondents with a job do not have significantly different behaviour than those without a job. However, if a respondent moved from not having a job to having one, this has a negative impact on the likelihood of using slow modes for family visits. The difference between the effect of employment status versus the effect of the change in it, leads us to think that moving into employment forces individuals to adjust their travel behaviour and using a car may provide a solution for the adjustment period. However additional data are required to further understand this process. All models predict that for those individuals with a job cars would be used more frequently rather than public transport, relative to those without a job. Two possible effects may be relevant to explain this: first, a possible income effect that differentiates between employed and unemployed respondents and second, having a job suggests a more complicated time schedule that might require a more flexible transport mode. The coefficients for distance between relatives is relatively straight forward: as expected, distance has a negative effect on the likelihood of using slow modes for travel, relative to cars. This is the case for the both the within as well as the between-effect: hence, persons living closer to their relatives will use slow modes more frequently relative to cars, and also respondents who moved during the panel period closer, have higher likelihood of using slow modes. This conclusion is in accordance with hypothesis 1. On the other hand, the coefficient for the effect of distance on public transport is significant

but almost zero. We suspect that the main reason for this result is technical: due to sample size considerations the dependent variable public transport combines tram and bus travel, which is mostly relevant to intra-city travel with train travel, which is usually an inter-city travel mean, as one mode of travel.

Common to all models is the finding that having at least one child has a negative effect on the likelihood of using public transport relative to car use. This is indeed in line with the expectations of hypothesis 2: the more people who travel, the greater the public transport costs and the greater the difficulty of using the transit system. This expectation is also confirmed by effect of respondents living with a partner (compared to single respondents), which is also negative for using public transport relative to cars. Though in the latter case, the effect of additional adults in the household may have to do with a positive income effect that, as already stated above, pushes for more car use and less public transport use.

Models 5 through 8 contain two additional results: In partial concurrence with hypothesis 3, according to these models having a child younger than 6 years old indeed leads to a lower likelihood of using public transport relative to using a car. However there is no significant effect of having young children on the propensity to use slow modes. The second result contradicts our previous findings regarding the effect of number of children: models 5 through 8 show that having at least two children has a positive effect on the likelihood of using public transport relative to car use. From this follows that households with at least two children are more likely to choose public transport compared with families with one child, which runs against our argument that the greater the household size is, the less public transport use we would expect. Finally, none of the models show significant effects of using slow modes relative to cars in any of these three variables, which is in accordance with our hypothesis.

Six variables measure the type of urbanity of trip origin and trip destination of a visit: three for each location. In all relevant models (models 3, 4, 7 and 8) variables pertaining to the urbanity of origin levels are jointly significant (p=0.00). Variables measuring urbanity at the destination are jointly significant in models 7 and 8 (p=0.00), while only marginally significant in model 3 (p=0.09) and insignificant in model 4.

From models 4 and 8 it emerges that variables related to high density at the origin (high address density, small average household size and low number of cars per household) have positive log-odds for choosing public transport, in line with hypothesis 4. From model 8 it appears that respondents who moved to areas of a high average number of cars per household (i.e. car intensive areas) have a negative log-odds for choosing public transport relative to cars. The effect measured in the baseline model (model 7) stems from this within-effect. Observing model 4 we learn that moving to a low density area appears to be negatively correlated with the likelihood of using slow modes, while the between-effect is insignificant. Apart from that, none of the origin variables have significant log-odds for choosing slow modes.

The results regarding the type of urbanity of the destination are more mixed. From model 8 we conclude that there is an inverse relationship between density and slow mode use. The between-effects for traveling to destinations in high density areas show negative log odds with respect to slow modes – respondents travelling to high density area have a lower likelihood of using slow modes compared to those traveling to medium density areas. The within-effects of model 8 show that when the destination of the visit changes to an area with lower average household size (typically highly urban areas), again, the log-odds for using slow modes are negative. As expected, when the destination changes to areas with a high average household size the log-odds for public transport are negative.

To summarize, we find strong evidence for the direct relationship between car use and distance, relative to slow modes (hypotheses 1) and for the positive effect of density on public transport use relative to car use (hypothesis 4). For the other two hypotheses the evidence is mixed. The effect of household size on public transport use relative to cars (hypothesis 2) is not conclusive: living with a partner does decrease the likelihood of using public transport relative to cars while not all models predict this for having children in the household. Having children under 6 (hypothesis 3) was found to have a positive effect on car use relative to public transport but not relative to slow modes.

More generally, variables attempting to predict slow mode travel appear to be less significant than when predicting public transport use. This may have to do with the fact that distance is probably the crucial determinant for slow mode usage. Another general finding is that in our within-between specification there were hardly any significant within-effects predicting public transport use. This may have to do with characteristics of our sample, in which very few respondents tended to shift to and from public transport usage, and very few moved to and from areas that are characterized by high public transport usage. But this may also hint that the divide between users and non-users of public transport is to a certain extent determined along time-constant individual and household characteristics.

CONCLUSIONS AND DISCUSSION

In this paper we investigated the determinants of mode choice decision of individuals who travel to visit relatives. We made two contributions to travel behaviour research: an empirical contribution and a methodological one. To our knowledge this is the first paper to focus entirely on mode choice decisions for traveling within the family network. While previous studies did not pay sufficient attention to these journeys, we argued that this type of travel has unique characteristics which sets it apart from other types of travel in general, and specifically from leisure travel. In our empirical analysis we made use of internet based panel data from the Netherlands, collected in three waves, which we have used to show the effects of individual and household characteristics, distance and degree of urbanization on the likelihood of choosing alternatives to car travel – walking, cycling or public transport. We have analysed two types of visits: one where children visit their parents and the second where siblings visit each other. Our main findings are that living with a partner, having at least one child and having a child under 6 years old, all affect negatively the likelihood of using public transport for family visits. In the Netherlands, distance is the main explanatory variable for the use of walking or cycling: the shorter the distance the higher the likelihood of using slow modes instead of a car. Those living in high degrees of urbanization have a positive log-odds for using public transport relative to cars compared with those living in lower densities. Degree of urbanization at the trip-origin has no significant correlation with traveling by walking or cycling, while at the destination it is negatively correlated with the use of slow modes.

Beyond empirical results we also made a methodological argument: unobserved heterogeneity is an often neglected aspect in the analysis of travel behaviour. Most researchers relied on cross-sectional data which do not allow accounting for preference on residence location and travel mode. In this paper we integrated available knowledge in order to benefit fully from the panel data at our hands and thus improve the estimation procedure. By choosing a Mundlak-type model specification we were able to provide estimates for time-varying variables as well as for time-constant variables while reducing the risk of correlation with unobserved variables. Despite having collected only three waves of data, in several cases the "within variation" was significant while the "between variation" was insignificant, especially the variables degree of urbanization at origin and destination and having a job. Collecting additional waves would increase the opportunity of discovering additional variables that display different within and between variation. Unfortunately we were not able to make much progress on the issue of potential endogeneity: the risk that distance between family members and the location of residence is affected by mode choice. While we added variables that partially mitigate the problem, we acknowledge that this by no means fully addresses the problem. For future research we would like to stress the importance of putting more research effort into these methodological issues, which will greatly enhance the precision and the reliability of future results.

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Table 1: Descriptive statistics for continuous variables

	Child-parent visits			Sibling visits		
Variable	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**
Age	3,497	42.9	8.7	6,318	45.7	8.7
Distance to relative (km)	3,497	32.0	50.2	6,318	41.0	52.0

Table 2: Descriptive statistics for categorical variables

		Child-Parent visits					Sibling visits				
Variable		**N**	**%**	**Car**	**Slow**	**PT**	**N**	**%**	**Car**	**Slow**	**PT**
Total		**3,497**	**100**	**71.0**	**24.4**	**4.6**	**6,318**	**100**	**77.7**	**18.0**	**4.3**
Sex	Male	1,466	41.9	74.1	21.1	4.8	2,619	41.5	77.7	17.8	4.5
	Female	2,031	58.1	68.8	26.7	4.5	3,699	58.5	77.6	18.2	4.2
Education	Low: Primary + VMBO	782	22.4	67.4	28.9	3.7	1,697	26.9	75.6	21.0	3.4
	Medium: HAVO/VWO/MBO	1,407	40.2	69.4	27.2	3.5	2,366	37.5	77.0	20.2	2.8
	High: HBO + WO	1,308	37.4	74.9	18.7	6.4	2,255	35.7	79.9	13.5	6.6
Living with partner	No	638	18.2	63.6	24.8	11.6	1,131	17.9	70.4	18.2	11.4
	Yes	2,859	81.8	72.7	24.3	3.1	5,187	82.1	79.2	18.0	2.8
Number of children under 18	0	1,791	51.2	70.2	22.5	7.3	3,572	56.5	76.3	17.7	6.0
	1	588	16.8	69.7	29.4	0.9	1,009	16.0	80.7	18.2	1.1
	2	807	23.1	73.2	24.2	2.6	1,300	20.6	78.5	18.6	2.9
	3 or more	311	8.9	72.0	26.1	1.9	437	6.9	79.4	18.3	2.3
Has a child under age 6	No	2,865	81.9	69.6	25.1	5.3	5,448	86.2	76.5	18.6	4.9
	Yes	632	18.1	77.5	20.9	1.6	870	13.8	84.7	14.6	0.7
Has a job	No	668	19.1	62.9	28.1	9.0	1,270	20.1	75.4	18.8	5.8
	Yes	2,829	80.9	72.9	23.5	3.6	5,048	79.9	77.7	18.0	4.3
type of urban	Rural	1,776	50.8	70.4	25.5	4.2	3,417	54.1	77.7	18.9	3.3

environment at age 15											
	Suburban	812	23.2	71.9	25.0	3.1	1,365	21.6	79.3	17.4	3.4
	Urban	909	26.0	71.4	20.6	8.0	1,536	24.3	76.1	16.5	7.4
<u>Trip origin:</u>											
Degree of urbanization of postcode area (address density)	Low (<500 address per km^2)	1,197	34.2	71.9	26.8	1.3	2,490	39.4	80.9	17.6	1.5
	Medium (500-1500)	1,245	35.6	73.9	23.2	2.9	2,065	32.7	79.1	18.3	2.6
	High (>1500)	1,055	30.2	66.5	22.9	10.5	1,763	27.9	71.4	18.4	10.3
Average household size in postcode	Low (under 2 persons)	565	16.2	66.0	19.8	14.1	918	14.5	66.8	19.5	13.7
	Medium (2-2.5)	1,852	53.0	69.8	26.4	3.9	3,344	52.9	78.1	18.4	3.6
	High (>2.5)	1,080	30.9	75.7	23.3	0.9	2,056	32.5	81.9	16.8	1.4
Average car ownership per household in postcode	Low (<1.0 cars per household)	1,585	45.3	67.6	24.4	8.1	2,569	40.7	71.0	20.6	8.4
	High (>=1.0)	1,912	54.7	73.9	24.4	1.8	3,749	59.3	82.2	16.2	1.6
<u>Trip destination:</u>											
Degree of urbanization of postcode area (address density)	Low (<500 address per km^2)	1,354	38.7	74.4	22.4	3.3	2,467	39.1	79.7	18.4	1.9
	Medium (500-1500)	1,110	31.5	68.3	26.9	4.8	1,786	28.3	75.8	21.1	3.1
	High (>1500)	1,043	29.8	69.5	22.5	7.8	2,065	32.7	76.9	14.9	8.2
Average household size in postcode	Low (under 2 persons)	615	17.6	70.6	18.9	10.6	1,315	27.6	74.5	15.9	9.7
	Medium (2-2.5)	2,128	60.9	71.9	23.5	4.6	3,261	51.6	79.5	17.2	3.3
	High (>2.5)	754	21.6	69.0	28.8	2.3	1,742	20.8	76.6	21.1	2.3
Average car ownership per household in postcode	Low (<1.0 cars per household)	1,696	48.5	69.6	23.8	6.6	2,949	46.7	75.5	17.7	6.9
	High (>=1.0)	1,801	51.5	72.4	23.9	3.8	3,369	53.3	79.6	18.3	2.1

Table 3: Multinomial regression results for mode choice. Dependent variable: mode of travel for family visits (base category: car)

MODEL	**1**		**2**			
	Pooled (Baseline)		**Within** $(z_i - \bar{z})$		**Between** $(x_i, \bar{z})$	
VARIABLES	**Slow Mode**	**PT**	**Slow Mode**	**PT**	**Slow Mode**	**PT**
Sex (base: male)	0.301*	-0.010			0.305*	-0.030
	(0.162)	(0.255)			(0.164)	(0.260)
Education (base: middle)						
High	0.225	0.409			0.219	0.423
	(0.188)	(0.282)			(0.189)	(0.287)
Low	-0.395**	0.188			-0.403**	0.182
	(0.183)	(0.335)			(0.184)	(0.338)
Age	0.108	-0.249**	0.330	-0.185	0.098	-0.254**
	(0.095)	(0.118)	(0.204)	(0.301)	(0.100)	(0.125)
Age squared	-0.001	0.003**	-0.003	0.003	-0.001	0.003*
	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)
Has child under 6	0.035	-0.693	-0.252	-0.535	0.094	-0.677
	(0.219)	(0.467)	(0.224)	(0.733)	(0.262)	(0.532)
Num. children under 18:						
At least 1 child	0.039	-0.836*	-0.049	0.447	0.064	-0.961*
	(0.206)	(0.451)	(0.166)	(0.772)	(0.242)	(0.533)
At least 2 children	-0.193	0.604	-0.071	0.391	-0.241	0.702
	(0.210)	(0.511)	(0.190)	(0.345)	(0.248)	(0.614)
At least 3 children	0.308	-0.908	0.260	-1.827	0.342	-0.866
	(0.285)	(0.834)	(0.211)	(1.747)	(0.309)	(0.883)
Partner in household	-0.139	-1.091***	0.273	-0.287	-0.178	-1.142***
	(0.202)	(0.261)	(0.418)	(0.368)	(0.216)	(0.279)
Has job	-0.292	-1.026***	0.006	-0.121	-0.338*	-1.162***
	(0.180)	(0.276)	(0.214)	(0.315)	(0.198)	(0.322)
Distance	-0.299***	0.009***	-0.274***	-0.002	-0.300***	0.009***
	(0.040)	(0.002)	(0.042)	(0.002)	(0.040)	(0.002)
Urban environment at age 15 (base= rural)						
City	-0.446**	0.527*			-0.447**	0.522*
	(0.189)	(0.272)			(0.191)	(0.273)
Suburb	-0.127	-0.466			-0.138	-0.479
	(0.182)	(0.345)			(0.182)	(0.346)
Constant	-2.635	3.572			-2.369	3.876
	(2.006)	(2.442)			(2.134)	(2.600)

Observations	3,497	3,497			3,497	3,497
Pseudo R	0.333	0.333			0.337	0.337
ll	-1720	-1720			-1711	-1711
df_m	28	28			46	46
chi2	171.5	171.5			202.6	202.6
AIC	3,500	3,500			3,518	3,518
BIC	3,684.79	3,684.79			3,813.67	3,813.67

MODEL	**3**		**4**			
	Pooled (Baseline)		**Within** $(z_i - \bar{z})$		**Between** $(x_i, \bar{z})$	
VARIABLES	**Slow Mode**	**PT**	**Slow Mode**	**PT**	**Slow Mode**	**PT**
Sex (base: male)	0.284*	0.145			0.285*	0.139
	(0.165)	(0.256)			(0.168)	(0.260)
Education (base: middle)						
High	0.177	0.177			0.165	0.174
	(0.191)	(0.290)			(0.194)	(0.293)
Low	-0.399**	0.013			-0.410**	0.003
	(0.188)	(0.345)			(0.190)	(0.349)
Age	0.108	-0.234**	0.341*	-0.214	0.094	-0.234*
	(0.095)	(0.119)	(0.203)	(0.330)	(0.102)	(0.126)
Age squared	-0.001	0.003**	-0.003	0.003	-0.000	0.003*
	(0.001)	(0.001)	(0.002)	(0.004)	(0.001)	(0.002)
Has child under 6	0.029	-0.539	-0.258	-0.546	0.072	-0.503
	(0.222)	(0.432)	(0.223)	(0.742)	(0.269)	(0.495)
Num. children under 18:						
At least 1 child	0.047	-0.732	-0.080	0.502	0.078	-0.874*
	(0.210)	(0.448)	(0.165)	(0.801)	(0.249)	(0.531)
At least 2 children	-0.202	0.666	-0.010	0.452	-0.248	0.744
	(0.216)	(0.523)	(0.166)	(0.504)	(0.256)	(0.622)
At least 3 children	0.281	-0.507	0.136	-1.818	0.315	-0.341
	(0.295)	(0.662)	(0.150)	(1.652)	(0.322)	(0.669)
Partner in household	-0.115	-0.791***	0.257	-0.292	-0.149	-0.827***
	(0.209)	(0.269)	(0.389)	(0.393)	(0.226)	(0.290)
Has job	-0.271	-0.827***	-0.083	-0.119	-0.309	-0.941***
	(0.183)	(0.276)	(0.218)	(0.304)	(0.204)	(0.325)
Distance	-0.294***	0.009***	-0.262***	-0.002	-0.297***	0.009***
	(0.040)	(0.002)	(0.042)	(0.003)	(0.040)	(0.002)
Urban environment at age 15 (base= rural)						
City	-0.429**	0.003			-0.452**	-0.009
	(0.218)	(0.338)			(0.223)	(0.341)
Suburb	-0.148	-0.451			-0.175	-0.474
	(0.189)	(0.349)			(0.191)	(0.352)

URBANITY AT ORIGIN						
Address density:						
(base: 500-1500 addresses						
per km^2)						
Low (<500)	0.133	-0.448	1.624**	0.091	0.100	-0.474
	(0.232)	(0.473)	(0.652)	(0.290)	(0.243)	(0.510)
High (>1500)	0.271	0.629*	-0.607	-0.067	0.321	0.613*
	(0.228)	(0.347)	(0.621)	(0.202)	(0.240)	(0.355)
Average household size						
(base: 2-2.5 persons)						
Low (<2)	0.037	0.379	0.975	-0.055	0.028	0.352
	(0.263)	(0.267)	(0.728)	(0.137)	(0.275)	(0.277)
High (>2,5)	-0.295	-0.766	-0.223	0.005	-0.296	-0.775
	(0.217)	(0.479)	(0.698)	(0.268)	(0.225)	(0.511)
Average car ownership	-0.020	-0.385	-0.012	-0.011	0.013	-0.494
(base: <1 cars per						
household)						
	(0.211)	(0.380)	(0.189)	(0.493)	(0.247)	(0.449)
URBANITY AT						
DESTINATION						
Address density:						
(base: 500-1500 addresses						
per km^2)						
Low (<500)	-0.199	-0.305	-0.662	-0.099	-0.170	-0.317
	(0.244)	(0.368)	(1.202)	(0.165)	(0.252)	(0.379)
High (>1500)	-0.179	0.371	-2.753*	-0.231	-0.194	0.395
	(0.222)	(0.336)	(1.482)	(0.229)	(0.229)	(0.349)
Average household size						
(base: 2-2.5 persons)						
Low (<2)	-0.422*	0.503	2.450*	0.200	-0.457*	0.485
	(0.256)	(0.335)	(1.263)	(0.220)	(0.265)	(0.345)
High (>2,5)	0.422*	-0.409	1.943	0.212	0.387*	-0.440
	(0.230)	(0.444)	(1.529)	(0.240)	(0.234)	(0.460)
Average car ownership	-0.245	0.629	-0.406	-0.146	-0.291	0.663*
(base: <1 cars per	(0.237)	(0.390)	(1.573)	(0.321)	(0.246)	(0.396)
household						
Constant	-2.505	2.158			-2.123	2.360
	(2.019)	(2.486)			(2.162)	(2.644)
Observations	3,497	3,497			3,497	3,497
Pseudo R	0.356	0.356			0.363	0.363
ll	-1660	-1660			-1645	-1645
df_m	48	48			86	86
chi2	248.2	248.2			309.1	309.1
AIC	3,416	3,416			3,466	3,466
BIC	3,711.67	3,711.67			4,008.05	4,008.05

MODEL	**5**			**6**		
	Pooled (Baseline)		**Within** $(z_i - \bar{z})$		**Between** $(x_i, \bar{z})$	
VARIABLES	**Slow Mode**	**OV**	**Slow Mode**	**PT**	**Slow Mode**	**PT**
Sex (base: male)	0.179	0.043			0.182	0.050
	(0.156)	(0.247)			(0.158)	(0.249)
Education (base: middle)						
High	0.256	0.617**			0.252	0.634**
	(0.189)	(0.270)			(0.191)	(0.272)
Low	-0.279	0.171			-0.281	0.154
	(0.176)	(0.339)			(0.177)	(0.343)
Age	-0.042	-0.228*	0.188	-0.656**	-0.062	-0.213*
	(0.093)	(0.118)	(0.192)	(0.331)	(0.099)	(0.125)
Age squared	0.001	0.002*	-0.002	0.007*	0.001	0.002
	(0.001)	(0.001)	(0.002)	(0.004)	(0.001)	(0.001)
Has child under 6	-0.060	-1.705***	-0.178	-0.227	-0.039	-1.891***
	(0.224)	(0.605)	(0.143)	(1.103)	(0.271)	(0.708)
Num. children under 18:						
At least 1 child	-0.065	-1.233**	-0.185	0.208	-0.043	-1.679**
	(0.220)	(0.514)	(0.248)	(0.421)	(0.275)	(0.758)
At least 2 children	0.035	1.154**	0.000	0.204	0.042	1.716**
	(0.223)	(0.544)	(0.234)	(0.252)	(0.280)	(0.826)
At least 3 children	-0.005	0.084	0.471	0.534	-0.074	-0.115
	(0.267)	(0.467)	(0.288)	(0.606)	(0.307)	(0.584)
Partner in household	0.053	-1.292***	0.585	-0.002	-0.000	-1.352***
	(0.201)	(0.252)	(0.447)	(0.643)	(0.216)	(0.263)
Has job	-0.019	-0.594**	-0.466**	-0.029	0.038	-0.658**
	(0.194)	(0.262)	(0.199)	(0.348)	(0.213)	(0.294)
Distance	-0.243***	0.007***	-0.224***	0.001	-0.244***	0.007***
	(0.032)	(0.002)	(0.034)	(0.006)	(0.032)	(0.002)
Urban environment at age 15 (base= rural)						
City	-0.174	0.714***			-0.178	0.703***
	(0.184)	(0.258)			(0.184)	(0.259)
Suburb	0.159	-0.048			0.152	-0.063
	(0.190)	(0.337)			(0.192)	(0.340)
Constant	0.441	2.798			0.844	2.608
	(1.903)	(2.480)			(2.030)	(2.644)
Observations	6,318	6,318			6,318	6,318

Pseudo R	0.348	0.348			0.352	0.352
ll	-2638	-2638			-2623	-2623
df_m	28	28			46	46
chi2	178.4	178.4			198.5	198.5
AIC	5,336	5,336			5,342	5,342
BIC	5,538.54	5,538.54			5,666.06	5,666.06

MODEL		**7**			**8**	
	Pooled		**Within** $(z_i - \bar{z})$		**Between** $(x_i, \bar{z})$	
VARIABLES	**Slow Mode**	**PT**	**Slow Mode**	**PT**	**Slow Mode**	**PT**
Sex (base: male)	0.165	0.170			0.172	0.174
	(0.159)	(0.255)			(0.161)	(0.257)
Education (base: middle)						
High	0.217	0.309			0.210	0.305
	(0.190)	(0.275)			(0.192)	(0.275)
Low	-0.285	0.052			-0.285	0.039
	(0.177)	(0.343)			(0.179)	(0.342)
Age	-0.049	-0.208*	0.170	-0.543	-0.066	-0.192
	(0.095)	(0.125)	(0.198)	(0.380)	(0.102)	(0.133)
Age squared	0.001	0.002	-0.002	0.006	0.001	0.002
	(0.001)	(0.001)	(0.002)	(0.004)	(0.001)	(0.002)
Has child under 6	-0.049	-1.411**	-0.162	-0.200	-0.015	-1.517**
	(0.226)	(0.608)	(0.131)	(1.508)	(0.276)	(0.658)
Num. children under 18:						
At least 1 child	-0.063	-1.266**	-0.175	0.235	-0.040	-1.680**
	(0.218)	(0.538)	(0.252)	(0.491)	(0.274)	(0.763)
At least 2 children	0.043	1.233**	-0.012	0.231	0.038	1.752**
	(0.221)	(0.571)	(0.240)	(0.272)	(0.279)	(0.833)
At least 3 children	0.009	0.188	0.490*	0.599	-0.054	-0.029
	(0.270)	(0.443)	(0.293)	(0.649)	(0.311)	(0.551)
Partner in household	0.148	-1.003***	0.616	0.008	0.106	-1.060***
	(0.204)	(0.261)	(0.471)	(0.707)	(0.219)	(0.272)
Has job	-0.030	-0.579**	-0.460**	0.014	0.034	-0.671**
	(0.199)	(0.290)	(0.202)	(0.342)	(0.219)	(0.332)
Distance	-0.242***	0.007***	-0.225***	-0.001	-0.244***	0.007***
	(0.032)	(0.002)	(0.035)	(0.007)	(0.032)	(0.002)
Urban environment at age 15 (base=						

rural)						
City	-0.269	0.294			-0.275	0.268
	(0.208)	(0.280)			(0.210)	(0.282)
Suburb	0.166	-0.057			0.175	-0.083
	(0.199)	(0.377)			(0.203)	(0.379)
URBANITY AT ORIGIN						
Address density: (base: 500-1500 addresses per km^2)						
Low (<500)	0.137	0.022	-0.594	1.215	0.150	-0.097
	(0.215)	(0.375)	(0.722)	(1.138)	(0.223)	(0.401)
High (>1500)	0.224	0.540	0.480	-0.196	0.209	0.585*
	(0.217)	(0.342)	(1.123)	(1.010)	(0.224)	(0.354)
Average household size (base: 2-2.5 persons)						
Low (<2)	0.196	0.521*	0.347	1.064	0.187	0.499*
	(0.263)	(0.300)	(1.267)	(1.002)	(0.272)	(0.301)
High (>2,5)	-0.173	-0.266	0.449	0.267	-0.178	-0.331
	(0.188)	(0.363)	(0.867)	(1.194)	(0.193)	(0.381)
Average car ownership	-0.296	-0.766*	0.059	-1.352*	-0.338	-0.658
(base: <1 cars per household)	(0.242)	(0.395)	(0.221)	(0.706)	(0.267)	(0.443)
URBANITY AT DESTINATION						
Address density: (base: 500-1500 addresses per km^2)						
Low (<500)	-0.124	-0.020	-1.068	0.150	-0.126	0.011
	(0.192)	(0.381)	(0.774)	(0.694)	(0.197)	(0.390)
High (>1500)	-0.370*	0.382	-0.499	0.473	-0.389*	0.377
	(0.221)	(0.284)	(0.595)	(1.186)	(0.228)	(0.291)
Average household size (base: 2-2.5 persons)						
Low (<2)	0.200	0.544**	-1.517**	1.309	0.258	0.530*
	(0.246)	(0.266)	(0.619)	(0.982)	(0.256)	(0.276)
High (>2,5)	0.378**	0.006	-1.062	-1.586*	0.403**	0.034
	(0.176)	(0.300)	(0.750)	(0.848)	(0.179)	(0.310)
Average car	-0.167	-0.236	-0.020	0.988	-0.141	-0.264
ownership (base: <1 cars per household)	(0.211)	(0.332)	(0.476)	(0.748)	(0.220)	(0.349)

Constant	0.692	1.631	1.000	1.435
	(1.951)	(2.671)	(2.102)	(2.840)
Observations	6,318	6,318	6,318	6,318
Pseudo R	0.377	0.377	0.382	0.382
ll	-2522	-2522	-2502	-2502
df_m	48	48	86	86
chi2	257.7	257.7	303.6	303.6
AIC	5,140	5,140	5,180	5,180
BIC	5,464.06	5,464.06	5,774.10	5,774.10