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Travel pattern transitions: Applying latent transition analysis within the mobility biographies framework

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A R T I C L E I N F O

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A B S T R A C T

This paper applies the relatively new method of latent transition analysis within the mobility biographies framework to assess how life events influence changes in travel behaviour. Using transition analysis, it is assessed how people switch between different travel patterns over time. Data from the first three waves of the Netherlands Mobility Panel (MPN) are used to reveal different travel patterns and analyse transitions between these patterns over time. Six different meaningful travel patterns are revealed. Four exogenous variables and six life events within the household, employment and residential biography are included to assess their effects on people's transitions between the travel patterns over time. For all life events significant effects are found, indicating that there might indeed be 'windows of opportunity' to change travel behaviour when a life event occurs. The results show that, on average, people who only use a single mode are less likely to change their travel pattern compared to multimodal travellers. In addition, the effects of life events and exogenous variables depend on the initial travel pattern. In general, single-mode travellers are less affected by life events than multimodal travellers. This indicates that it is important to include past travel behaviour within mobility biographies studies.

1. Introduction

Travel behaviour can generally be described as inert or habitual behaviour; it does not change very often (Chorus and Dellaert, 2010; Gärling and Axhausen, 2003). It is therefore interesting to gain more insight into when travel behaviour does change. Since a lot of travel behaviour studies are based on cross-sectional data, any events leading up to changes cannot be modelled. A relatively new approach to study travel behaviour change is the mobility biographies approach. Mobility biographies studies take a life-course approach and assume there are certain key events (life events) in an individual's life course that trigger change in travel behaviour (Lanzendorf, 2003). Mobility biographies studies are often based on longitudinal data to analyse individual changes over time.

These life events have been described as 'windows of opportunity' to change everyday routines (Schäfer et al., 2012). Multiple studies have shown that people are indeed more susceptible to interventions after life events such as a residential move or changing jobs (Anable, March 2013; Thøgersen, 2012; Verplanken and Roy, 2016). Recent overviews of mobility biographies studies are provided by Müggenburg et al. (2015) and Schoenduwe et al. (2015). Knowledge about these windows of opportunity could benefit transport policy that is aimed at changing travel behaviour or realizing a modal shift.

Most mobility biographies studies are, however, of a very explorative nature and do not consider the events and their effects in a

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broader theoretical framework (Müggenburg et al., 2015). A number of theoretical frameworks have been proposed over the years (Clark et al., 2014; Lanzendorf, 2003; Müggenburg et al., 2015; Scheiner, 2007). All frameworks are comparable in the fact that they distinguish different domains of life events that might have an influence on an individual's travel behaviour. Scheiner (2007) distinguishes three domains of life events that interact with the mobility biography; events in the household biography, the employment biography and the residential biography. Besides effects on the mobility biography, Scheiner (2007) argues that there are interrelations between the domains of life events. An important extension to this, as well as the other frameworks is given by Clark et al. (2014) who proposes that the deliberation of travel behaviour that takes place after certain life events is influenced by mediating factors, such as an individual's personal history (e.g. initial travel behaviour) and intrinsic motivations (e.g. economic reasons). Most mobility biographies studies, however, only assess the direct effects of life events on travel behaviour and often do not consider the interaction with past travel behaviour. Some mobility biographies studies do include past travel behaviour (see e.g. Prillwitz et al. (2006), Scheiner and Holz-Rau (2013) and Yamamoto (2008)), but they often do not consider interactions between past travel behaviour and the effects of life events (with the exception of Kroesen (2014)). To date, there is therefore limited empirical support for the mediating factors (in terms of initial travel behaviour) as proposed by Clark et al. (2014).

This paper aims to apply the relatively new latent class transition analysis within the mobility biographies framework to reveal different travel patterns and assess the influence of life events on changes in travel behaviour. This is done by extending the latent class model to a latent transition model. While traditional clustering techniques deterministically assign people to clusters, latent class analysis takes measurement error into account by probabilistically assigning people to clusters. Latent class- and transition analysis have already successfully been used to identify different types of multimodal travellers (Molin et al., 2016) and to assess the influence of several exogenous variables on changes in travel behaviour (Kroesen, 2014).

The first contribution of this study is that it applies a latent clustering- and transition analysis within the mobility biographies framework. This paper considers travel patterns, defined by self-reported trip rates, instead of the use or ownership of a single mode. Most mobility biographies studies only consider a single mode (see e.g. Clark et al. (2014) and Oakil et al. (2011)) or multiple modes in different models (see e.g. Beige and Axhausen (2012) and Scheiner and Holz-Rau (2013)). Only a limited number of studies consider multimodal travel patterns, see e.g. Kroesen (2014) and Scheiner et al. (2016). Considering multimodal travel patterns within the mobility biographies framework offers a holistic view of travel behaviour and the effects of life events. This also offers the possibility to assess how the use of different travel modes influences the probabilities that one will change its travel pattern, even without the occurrence of a life event. It can, for instance, be expected that people who use different modes, are more prone to change their behaviour since they are already familiar with multiple modes. Diana (2010) showed that multimodal travellers show a stronger propensity to use other modes, something that was also concluded by Kroesen (2014).

The second contribution is the fact that the influences of both life events and other exogenous variables on changes in travel patterns as a whole are assessed. Besides six life events (change in the number of adults in the household, changing jobs, stop working, moving house, birth of a child and start or changing education), nine exogenous variables are included in the analyses (gender, age, educational level, household composition, income, working hours per week, level of urbanization, distance to a train station and number of reported weekend days). While most mobility biographies studies include one or more exogenous variables, they do not consider the effects of these variables on changes in the travel pattern as a whole, but rather on a single mode, as explained in the previous paragraph. Besides having an influence on initial travel behaviour, it could be argued that several personal- and household characteristics have an influence on changes in travel behaviour. For instance, people with a low income may have fewer financial possibilities to change their travel behaviour and might show more inert behaviour compared to people with a higher income. The same holds for people living in rural areas where public transport is often less of an option than for people living in densely populated areas where there is often a better public transport network. Therefore, people in densely populated areas might show more changes in their travel behaviour. It can therefore be expected that these exogenous variables not only have an influence on an individual's initial travel pattern, but also on the transition probabilities.

The third contribution of this paper is that it considers the initial travel pattern of people when analysing changes in travel patterns and especially the interaction between past travel behaviour and life events. It has been argued that past behaviour is an important predictor of future behaviour (Ouellette and Wood, 1998). Although initial travel behaviour is sometimes included in mobility biographies studies, interactions between past travel behaviour and life events are often not. This paper explicitly considers interactions between life events and initial travel behaviour to assess whether effects of life events are different, depending on one's past travel behaviour.

2. Model conceptualization

Latent class- and transition analysis will be used to reveal different travel patterns and assess how transitions between these classes are influenced by the occurrence of different life events. Fig. 1 shows the conceptual model for the latent transition analysis.

At each point in time, a latent class model is specified to cluster respondents based on their similarities with respect to the included indicators. Latent class analysis is built on the assumption that the associations between the indicators are explained by an underlying latent variable (McCutcheon, 1987). The latent variable is not directly measured, but it is inferred from observed indicators. In this study, trip rates of different modes (car, bike, public transport and walking) are used as indicators. As a result, the latent categorical variable represents an individual's travel pattern.

After defining the different travel patterns, transitions between these patterns are assessed by extending the latent class model to a latent transition model. A latent transition model can be described as repeated latent cluster analyses over-time where the same travel

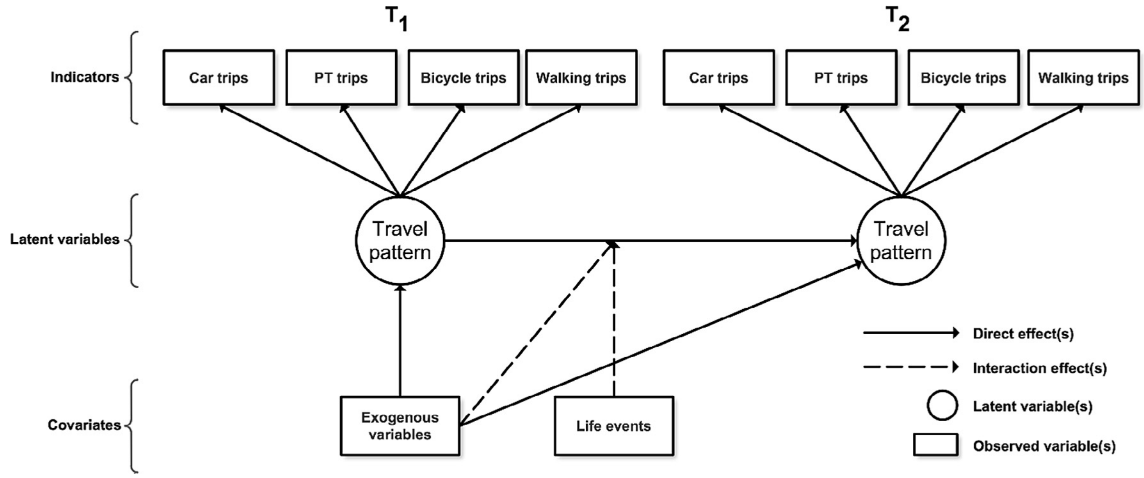

Fig. 1. Conceptual model of the latent class- and transition analysis.

patterns are defined at each time point to assess transitions between the patterns (Collins and Lanza, 2010). The parameter estimates from the latent transition analysis can be used to compute transition probability matrices.

Latent class- and transition analysis allow for the use of covariates (exogenous variables and life events). The exogenous variables are used to predict initial cluster membership and interact with transitions between clusters. The life events are only used to interact with transitions between clusters. The effects of the covariates are able to vary for every latent class (as indicated by the interaction effect in Fig. 1). By interacting life events and other exogenous variables with transitions, their effect on transition probabilities can be assessed by computing different transition matrices. Latent transition analysis thereby allows assessing whether people with different travel patterns are differently affected by life events.

In total, nine active covariates are included as predictors for initial cluster membership; gender, age, educational level, household composition, income, working hours per week, level of urbanization, distance to a train station and a variable to control for the number of reported weekend days. The life events are not used as predictors for initial cluster membership, but are assumed to influence the transitions between clusters.

Within the mobility biographies framework, three domains of life events are typically considered; events in the household biography, the employment biography and the residential biography (Schoenduwe et al., 2015). Within these three domains, six life events are included to assess their effects on transitions between travel patterns. With respect to the household biography a change in the number of adults and the birth of a child are included. A change in the number of adults could occur due to multiple life events such as partners who start living together or divorce. With respect to the employment biography changing jobs, stop working and starting or changing an educational programme are included. Finally, with respect to the residential biography a residential move is included.

3. Method

3.1. Data and method

To assess over-time changes of individuals, longitudinal data is required. In this study, panel data from the Netherlands Mobility Panel (MPN) are used. The MPN is an annual household panel that started in 2013 and consists of approximately 2000 households. Each year, household members of at least 12 years old are asked to complete a three-day travel diary and fill in a questionnaire that includes questions about different events in the past year. Every household is also asked to fill in a questionnaire about household related characteristics, such as information about household composition and ownership of means of transport. More information about the MPN can be found in Hoogendoorn-Lanser et al. (2015). Currently, data from the first three waves are available and used for the present analysis.

The occurrence of the different life events are directly measured in the questionnaires that respondents fill out every year. For changing jobs, stop working, a change in the number of adults in the household and a residential move, however, the occurrence is also calculated based on other changes that can be observed between waves to account for respondents forgetting to report the life event. For instance, if a respondent reported to be unemployed in wave 1, but reported to have a job in wave 2, he is treated as having changed jobs regardless of whether he reported this in the questionnaire. The other way around goes for stop working. A change in the number of adults in the household is measured through a change in the reported household composition, while a residential move is also calculated based on a change in the respondents' postal code.

Travel patterns can be defined in different ways. Different types of indicators can be used to distinguish the different patterns. In this study trip rates of four modes are used. In the MPN travel diary all trips are reported including the mode, distance and duration of the trip. Due to the self-reported nature of the travel diary, distance and duration might be biased due to rounding errors (Rietveld, 2001). The trip rate is assumed to be the most accurate reported indicator. The trip rates are count variables. Their distributions can therefore be approximated by the Poisson distribution and Poisson regression models can be used to model the relationships between the latent class variable and the indicators (Vermunt and Magidson, 2002).

If a multi-modal trip is reported, only the main mode of transport is considered to estimate the different clusters. Including access and egress modes would bias the data since the total trip rate of multi-modal clusters would seem higher compared to unimodal clusters. Furthermore, it would become unclear whether a mode is used as access or egress mode, or as the main mode of transport.

Although household members older than 12 years are asked to participate in the MPN, information about life events is not requested until respondents are at least 16 years old. Children younger than 16 years are therefore removed from the sample. The sample consists of 6880 respondents from 3921 households who completed at least one wave.

To uncover transitions between travel patterns, respondents should have completed at least two consecutive waves. In total there are 3807 respondents who completed at least two consecutive waves, of which 1711 completed all three waves. The data is organized as a pooled wave-pair sample, similar to the approach described by Golob (1990). The alternative to using a pooled-wave pair sample is using a pure-stayer sample, where only respondents who participated all three waves are included. An advantage of pooling wave-pairs over using a pure-stayer sample is the fact that no data is lost. Using a pure-stayer sample would decrease the sample size to 1711 individuals, while the wave-pair approach allows to include all 3807 respondents who completed at least two consecutive waves. Especially since life events do not occur regularly and their frequency is therefore rather low, removing data is not desired. The pooled wave-pair sample consists of 5518 wave pairs from 3807 respondents (2519 unique households).

A clear disadvantage of pooling wave-pairs is the fact that redundant information is present in the data for consecutive wave-pairs from the same respondent (Golob, 1990). Observations are therefore no longer independent. If no correction is applied, the wave-pairs would be treated as independent observations in the analysis. Besides dependencies due to pooling wave-pairs, there are also dependencies due to the fact that there are multiple respondents from the same household in the panel. Earlier studies have already shown that travel decisions are not independent between household members, see e.g. (Gliebe and Koppelman, 2005; Timmermans, 2009). The standard errors can be corrected for dependencies between observations by defining an independent observational unit (Vermunt and Magidson, 2016). If the respondents would be defined as the independent observational unit, the wave-pairs would no longer be assumed to be independent, but respondents from the same household would be. If the household would be defined as the independent observational unit, all observations within the household, both between household members and between wave-pairs, would not be assumed to be independent. Therefore, the household is treated as the independent observational unit.

The statistical software package Latent Gold is used to estimate both the latent class- and the latent transition models (Vermunt and Magidson, 2005). The latent class model is estimated using data from both waves simultaneously. Measurement invariance over time is therefore assumed. Unfortunately, Latent Gold does not support an analysis to test measurement invariance over time. Estimating two different latent class models for both waves separately showed, however, that the same clusters are present in both waves with only minimal differences.

To decide on the appropriate number of clusters, two methods are used, as described by Magidson and Vermunt (2004). The first method relies on the Bayesian Information Criterion (BIC). The BIC takes into account both model fit and parsimony. A model with a lower BIC is preferred over a model with a higher BIC. The second method uses the L^2 of the 1-class model as a baseline measure of the total amount of association in the data. By comparing the L^2 of the higher class models with the L^2 of the 1-class solution, the reduction in L^2 represents the total association that is explained by the model. When the amount of reduction of L^2 becomes relatively small, it is no longer justified to add an extra class to the model.

Although nine active covariates are used as predictors for initial cluster membership, not all are used to interact with transitions between waves. This would result in a high number of parameters which could lead to estimation problems. Therefore, besides the six life events, four covariates (gender, age, educational level and level of urbanization) are interacted with transitions. These covariates were chosen because they are also often taken into account in previous studies, see e.g. (Clark et al., 2014; Kroesen, 2014).

3.2. Descriptive statistics

Table 1 shows the measurement and distribution of variables in the sample. Age is included both as a standardized linear variable and the quadratic term of this variable to account for the non-linear effect of age. For simplicity reasons, the table only shows the mean and standard deviation of age. As can be seen, the frequency of the included life events is rather low. A decrease in the number of adults in the household shows the lowest occurrence rate with only 2.6%. Changing jobs is the most frequently observed life event with 8.9%.

4. Results

4.1. Travel patterns

As described in Section 3.1, the BIC and reduction of L^2 are used to decide on the appropriate number of clusters. A 1-class to 10-class model is estimated without any covariates to assess only the variance between the indicators. The BIC value suggests that a model with a least 10 classes would be appropriate. After the 6-class solution, however, the reduction of L^2 becomes rather small (less than 3%). This suggests that using a model with 6 classes would be appropriate to model the data. Since a model with a high number of classes would be hard to interpret, the 6-class model is used.

Table 2 presents the profiles of the 6-class model, including all covariates. Based on the Wald-statistics it can be concluded that

Table 1
Sample Composition (N = 5518 Wave Pairs).

Variable		
Indicators		
Car trip rate (over three days)	Mean (SD)	4.6 (4.3)
PT trip rate (over three days)	Mean (SD)	0.5 (1.3)
Bike trip rate (over three days)	Mean (SD)	2.5 (3.6)
Walking trip rate (over three days)	Mean (SD)	1.5 (2.6)
Active covariates		
Gender	Male	46%
	Female	54%
Age	Mean (SD)	46.7 (17.0)
Educational level	Low	26%
	Mid	40%
	High	34%
Working hours	Less than 12 h/week	25%
	12–35 h/week	31%
	35 + h/week	44%
Personal net income per year	No income	10%
	Less than €12,000	19%
	€12,000 - €24,000	36%
	€24,000 - €36,000	20%
	More than €36,000	5%
	Missing	10%
Level of urbanization	Urban (1500 + inhabitants/km^2)	48%
	Sub-urban (1000–1500 inhabitants/km^2)	24%
	Rural (less than 1000 inhabitants/km^2)	29%
No. HH-members 12-	Mean (SD)	0.3 (0.7)
No. HH-members 12+	Mean (SD)	2.3 (1.1)
Distance to train station (km)	Mean (SD)	3.4 (3.6)
No. of weekend days reported	Mean (SD)	0.9 (0.8)
Change in number of adults in HH (%)	Decrease	2.6%
	Increase	5.9%
Birth of a child (%)		3.3%
Changing jobs (%)		8.9%
Stop working (%)		4.9%
Start/change education (%)		4.0%
Residential move (%)		4.0%
Inactive covariates		
Car ownership		74%
PT card ownership		31%
Occupational status	Paid job	57%
	Student	8%
	Retired	19%
	Other	16%

the indicators and all active covariates, except gender, are significant. All indicators significantly differ between the classes and all active covariates, except gender, significantly affect class membership. Apparently, whether a respondent is male or female is no significant predictor of an individual's travel pattern. It can, however, be seen that the distribution of gender does differ among the classes.

The first and largest class (30% of the sample) represents strict car users. Besides making on average 8 trips by car in three days, they barely use other modes to travel. The strict car class is the only class with a higher share of men. Strict car users show the highest employment rate of 71%, with 44% of the class members working fulltime. A relatively high share of strict car users lives in rural areas. This could be explained because rural areas usually are not well-connected by public transport and distances are too large to travel by bike.

The second class (19% of the sample) are respondents who also show high car usage, but complement this with the bike. On average, they show a car trip rate of 1.6 trips lower compared to the strict car users, but besides car trips, they make over 4 trips by bike. Their overall trip rate is therefore higher than the strict car users. In terms of household composition, level of urbanization and education level, the second class is comparable with the first class. The second class, however, represents more women with a lower employment rate. The bike is primarily used for non-work related trips.

The third class (16% of the sample) consists of people who mostly use the bike. The bike class shows the highest share of females and a high share of people without a job. The class has a relatively high share (17%) of students. As expected, most respondents in this class live in urban areas. Over a third of respondents within this class are part of a 1-person household. Besides making almost 8 trips by bike in three days, they also occasionally use the car. The 0.8 car trips per three days translates to just under 2 trips per week (1 two-way trip).

The fourth class (13% of the sample) primarily make their trips by car or walking. They also make an occasional bike trip but

Table 2
Profiles Of The 6-Class Latent Class Model.

	Class[a]	SC	CB	B	CW	LM	PT
Indicators	Class size (%)	30	19	16	13	11	10
Trips by car (Wald = 1401, $p < .00$)	Mean	8.1	6.5	0.8	4.4	0.8	1.3
Trips by PT (Wald = 1456, $p < .00$)	Mean	0.1	0.1	0.3	0.2	0.0	3.4
Trips by bike (Wald = 1065, $p < .00$)	Mean	0.0	4.5	7.9	1.4	0.3	1.4
Trips by walking (Wald = 2997, $p < .00$)	Mean	0.5	0.6	1.2	6.3	0.2	1.5
Active covariates							
Gender (%) (Wald = 8 $p = .14$)	Male	53	45	38	42	48	45
	Female	47	55	62	58	52	55
Age (Wald = 183 $p < .00$)	Mean	46.8	49.4	44.3	53.3	47.1	36.5
Educational level (%)	Low	21	22	30	28	34	28
(Wald = 42 $p < .00$)	Mid	45	41	35	37	41	34
	High	34	37	35	35	25	38
Working contract (%)	Part-time (12–35 h/week)	26	31	24	25	20	19
(Wald = 79 $p < .00$)	Fulltime (> 35 h/week)	44	29	19	20	28	32
	No job (< 12 h/week)	30	40	57	55	53	50
Net income per year (%)	No income	4	7	17	9	13	18
(Wald = 62 $p < .00$)	Less than €12,000	12	18	28	19	22	27
	€12,000 to €24,000	42	35	29	38	35	27
	€24,000 to €36,000	24	23	14	21	14	18
	more than €36,000	6	6	3	5	4	4
	Missing	12	11	9	9	12	7
Level of urbanization (%)	Urban	40	40	56	51	49	66
(Wald = 70 $p < .00$)	Sub-urban	23	28	23	22	21	18
	Rural	36	32	21	27	30	16
Household members 12 years or older (%)	1	20	20	34	29	23	34
(Wald = 23 $p < .00$)	2	54	50	35	53	46	30
	3+	27	30	31	18	30	36
Children 12- in household (Wald = 39 $p < .00$)	%	23	21	14	16	16	6
Number of weekend days (Wald = 28 $p < .00$)	Mean	0.84	0.92	0.75	0.92	0.98	0.87
Distance to train station (Wald = 50 $p < .00$)	Mean (km)	3.9	3.5	2.8	3.3	3.5	2.5
Inactive covariates							
Car ownership (%)	One or more cars	94	88	47	79	67	37
PT card ownership (%)	One or more cards	16	23	45	31	22	78
Occupational status (%)	Paid job	71	62	46	46	49	50
	Student	2	4	17	2	6	32
	Retired	16	21	17	29	17	11
	Other	11	12	20	23	28	8
Car trip purpose	Working trips	2.3	1.2	0.1	0.7	0.2	0.3
	Shopping trips	1.5	1.3	0.1	1.0	0.2	0.2
	Leisure trips	2.2	2.3	0.4	1.6	0.3	0.6
	Other trips	2.0	1.6	0.2	1.1	0.1	0.2
PT trip purpose	Working trips	0.0	0.0	0.1	0.0	0.0	2.1
	Shopping trips	0.0	0.0	0.0	0.0	0.0	0.3
	Leisure trips	0.0	0.0	0.1	0.1	0.0	0.7
	Other trips	0.0	0.0	0.1	0.0	0.0	0.3
Bike trip purpose	Working trips	0.0	0.9	2.1	0.2	0.1	0.3
	Shopping trips	0.0	1.2	2.3	0.4	0.1	0.3
	Leisure trips	0.0	1.4	2.3	0.5	0.1	0.6
	Other trips	0.0	1.0	1.3	0.3	0.0	0.2
Walking trip purpose	Working trips	0.0	0.0	0.1	0.3	0.0	0.2
	Shopping trips	0.1	0.1	0.4	1.6	0.0	0.5
	Leisure trips	0.3	0.4	0.6	3.3	0.1	0.6
	Other trips	0.1	0.1	0.2	1.0	0.0	0.1
Distance (km)	Car	144.8	106.5	15.0	66.4	21.4	29.5
	PT	2.5	3.7	13.6	10.0	0.2	124.9
	Bike	0.1	12.5	23.4	4.3	1.2	4.4
	Walk	0.7	0.8	1.6	6.9	0.2	2.7

[a] SC: Strict Car, CB: Car and Bike, B: Bike, CW: Car and Walk, LM: Low Mobility, PT: Public Transport

rarely travel by public transport. The average age of this class is the highest of all classes. This is also reflected in the fact that this class shows the lowest employment rate and 29% of the people is retired. As a result, this class shows the highest leisure trip rate of all classes. People in this class walk on average 6.9 kilometres in three days. This is, compared to the walking distance of other classes, remarkably high.

The fifth class (11% of the sample) shows a very low overall trip rate. On average, people in this class only report a total of 1.3 trips in three days. The class shows a relatively high share of low-educated people (34%). Besides the low education level, there are

Table 3
Transition Matrices For Different Life Events.

Average transition probabilities							Residential move						
	SC	CB	B	CW	LM	PT		SC	CB	B	CW	LM	PT
Strict Car (SC)	0.70	0.13	0.00	0.05	0.09	0.02	SC	0.67	0.16	0.00	0.05	0.10	0.02
Car and Bike (CB)	0.23	0.53	0.13	0.05	0.05	0.01	CB	0.37	0.42	0.12	0.08	0.01	0.00
Bike (B)	0.02	0.14	0.74	0.03	0.03	0.04	B	0.03	0.16	0.72	0.02	0.02	0.05
Car and Walk (CW)	0.10	0.08	0.08	0.64	0.06	0.04	CW	0.05	0.12	0.07	0.30	0.27	0.19
Low Mobility (LM)	0.11	0.08	0.08	0.03	0.69	0.02	LM	0.12	0.09	0.08	0.28	0.41	0.01
Public Transport (PT)	0.08	0.04	0.02	0.07	0.12	0.67	PT	0.00	0.10	0.11	0.26	0.00	0.52
Decrease of the number of adults in HH							Birth of a child						
	SC	CB	B	CW	LM	PT		SC	CB	B	CW	LM	PT
Strict Car (SC)	0.67	0.14	0.01	0.08	0.09	0.00	SC	0.70	0.07	0.00	0.15	0.08	0.01
Car and Bike (CB)	0.15	0.62	0.15	0.00	0.01	0.07	CB	0.27	0.32	0.00	0.38	0.02	0.00
Bike (B)	0.00	0.02	0.88	0.00	0.04	0.05	B	0.03	0.16	0.12	0.64	0.05	0.00
Car and Walk (CW)	0.13	0.11	0.19	0.56	0.00	0.01	CW	0.21	0.39	0.00	0.31	0.00	0.09
Low Mobility (LM)	0.01	0.05	0.36	0.02	0.54	0.02	LM	0.36	0.08	0.04	0.04	0.45	0.03
Public Transport (PT)	0.35	0.12	0.03	0.01	0.00	0.48	PT	0.17	0.00	0.02	0.29	0.30	0.21
Increase of the number of adults in HH							Start or change of education						
	SC	CB	B	CW	LM	PT		SC	CB	B	CW	LM	PT
Strict Car (SC)	0.70	0.16	0.00	0.02	0.11	0.00	SC	0.77	0.03	0.00	0.07	0.01	0.11
Car and Bike (CB)	0.27	0.58	0.13	0.00	0.02	0.00	CB	0.29	0.27	0.18	0.06	0.16	0.04
Bike (B)	0.01	0.11	0.71	0.03	0.10	0.05	B	0.02	0.17	0.46	0.22	0.00	0.14
Car and Walk (CW)	0.11	0.00	0.18	0.64	0.07	0.00	CW	0.06	0.08	0.06	0.70	0.07	0.04
Low Mobility (LM)	0.02	0.02	0.14	0.04	0.74	0.04	LM	0.21	0.23	0.01	0.00	0.17	0.38
Public Transport (PT)	0.10	0.04	0.00	0.00	0.06	0.80	PT	0.03	0.02	0.00	0.01	0.40	0.55
Changing jobs							Stop working						
	SC	CB	B	CW	LM	PT		SC	CB	B	CW	LM	PT
Strict Car (SC)	0.66	0.20	0.00	0.05	0.05	0.04	SC	0.54	0.22	0.02	0.02	0.17	0.04
Car and Bike (CB)	0.29	0.45	0.15	0.04	0.05	0.01	CB	0.02	0.50	0.20	0.15	0.06	0.07
Bike (B)	0.15	0.14	0.60	0.01	0.04	0.05	B	0.00	0.06	0.69	0.14	0.06	0.04
Car and Walk (CW)	0.30	0.20	0.09	0.34	0.07	0.01	CW	0.01	0.03	0.08	0.79	0.05	0.05
Low Mobility (LM)	0.12	0.04	0.14	0.02	0.62	0.06	LM	0.05	0.04	0.02	0.15	0.74	0.00
Public Transport (PT)	0.05	0.09	0.02	0.05	0.33	0.47	PT	0.06	0.01	0.01	0.17	0.28	0.47

[*] To compute the transition matrices, all parameters from Table 4 are used, both the significant and non-significant parameters.

no remarkable characteristics that could explain the low mobility. The average number of weekend days reported is the highest for this class.

The sixth and smallest class (10% of the sample) represents multimodal travellers who primarily use public transport. The average age of this class is the lowest and it has the highest share of students (31%). However, since there is only one public transport class, different types of public transport users are grouped in this cluster. From the students who belong to this class, 85% works less than 12 h per week and 98% has a yearly income of less than €12.000. If students are not considered, 74% of public transport users have a job of at least 12 h per week and 51% is highly educated. It can therefore be concluded that two types of people belong to the public transport class; students and highly educated working people.

4.2. Latent transition analysis

The parameter estimates of the 6-class transition model can be found in Table 4 in the appendix. The parameters indicate the influence of variables on class membership in the next wave. A negative parameter indicates a decreasing probability of transitioning to the specific class and vice versa. The obtained parameters, as shown in Table 4 in the appendix, are used to compute different transition probability matrices for every combination of covariates and life events, using a multinomial logit model.

Table 3 shows the average transition probabilities of the sample. As expected, the unimodal classes (strict car and bike) show higher probabilities of staying in the same class compared to the more multimodal classes (car and bike, car and walk and public transport). All classes show a very low probability of going to the public transport class in the second wave. The bike and car/walk classes show the highest transition rates to public transport, but still with a probability of only 4%. Higher probabilities are shown towards the bike cluster, or the cluster that combines car with bike. All classes, except for the bike class, show a relatively high probability of becoming strict car users in wave 2 (ranging from 8% to 23%). This is in line with findings by Kroesen (2014).

In total, 72 significant parameters are found. Almost all constants have a significant negative parameter. This indicates that class membership has a positive effect on itself. In other words, initial class membership in wave 1 is a strong indicator for membership in the same class in wave 2. As expected, dependent on the initial travel pattern, effects of life events and other exogenous variables are different.

Since the main focus of this paper is on assessing the effect of life events on transitions between travel patterns, the effect of the other exogenous variables will not be discussed in detail. The found significant effects are, however, in line with expectation. For instance, for the effect of age it is found that strict car users tend to shift towards the car and walk profile at older age, while for the car and bike users the probability of becoming public transport users decreases at older age.

For all life events significant effects are found, indicating that there might indeed be ‘windows of opportunity’ to change travel behaviour when a life event occurs. The bold parameters in Table 4 in the appendix indicate significant effects. The effect on the average transition probabilities of the life events will shortly be discussed.

Besides the average transition probabilities for the whole sample, Table 3 also presents the average transition probabilities in case of the different life events. If the event does not occur, the transition matrix is almost identical to the average transition matrix of the whole sample. This can be explained by the low frequency of the life events in the sample. These matrices are therefore not shown.

For the change in the number adults in the household, a matrix for both a decrease and increase in the number of adults is shown. When the number of adults in the household decreases, the public transport users are most strongly affected by showing a strong increase in the probability of changing to a travel pattern where car plays an important role. Their probability of becoming a strict car user increases from 8% to 35% and the probability of becoming a car and bike user increases from 4% to 12%. The low mobility class, however, shows an increased probability of transitioning to the bike class from 8% to 36%. A decrease in the number of adults could represent an event such as a divorce. The remaining household member(s) has to make trips which were previously done by the partner and therefore the travel pattern has to be adjusted. Earlier research has shown that the loss of a partner is related to a decrease in household car ownership (Clark et al., 2014). It is therefore an unexpected result that public transport users show a large increase in probabilities of switching to a more car dependent travel pattern. However, other research found lagged effects from a divorce in the form of both a mode shift towards and a mode shift away from car (Oakil et al., 2011). This indicates that the effect of a decrease in the number of adults in the household is dependent on a number of variables. For example, if partners shared a car before splitting up, the partner that keeps the car now always has a car available, whereas the other partner is left with no car availability, until a new car is bought. Both partners will therefore probably show a different reaction to splitting up, in terms of travel behaviour. Further analysis is therefore needed to fully understand why the public transport users shift towards a class with relatively high car use.

An increase in the number of adults in the household, which could be because partners started living together, increases chances of remaining in the same travel pattern for the car and bike, low mobility and public transport class. For the remaining classes the probability of keeping the same travel pattern does not change much. Earlier studies also found that an increase in the number of adults in the household has little to no effect on travel behaviour. Beige and Axhausen (2012) found that changes in terms of mobility tools ownership (such as cars or public transport cards), are less likely when the household size increases, Oakil et al. (2011) found that cohabitation has no significant influence on a mode shift from or to car for commuting and Scheiner and Holz-Rau (2013) only found a small increase in the chance that people travel by car as passenger.

The overall effect of changing jobs is an increased probability of becoming a member of one of the three car classes. Except the public transport class, all classes show an increase in the probability of becoming a strict car user. The probability of becoming a car and walk user decreases. Oakil et al. (2011) also found that changing jobs leads to a mode shift to car, but also to a shift away from car, while Kroesen (2014) found that a change of jobs is associated with an increase in public transport use (although it should be noted that Kroesen used data from the 1980s making it somewhat harder to compare results). A remarkable and unexpected effect is observed for the public transport class. The probability of transitioning to the low mobility class increases with 20%. A new job, or changing jobs, usually implies that work trips have to be made, while the low mobility class represents almost no trips. In-depth analysis (results not shown) revealed that most of the public transport users with a new job who transition toward the low mobility class increased their working hours due to the new job. The fact that they became a member of the low mobility class is therefore unexpected. It might indicate that these respondents started working from home in their new job. It is, however, not expected that this is true for all respondents. A more plausible explanation could be the fact that, because they have less free time due to the increase in working hours, they show a form of soft refusal and underreport their trips. The presence of possible soft refusal in the MPN has been shown in de Haas et al. (2017), but more research is needed to confirm that the observed shift towards the low mobility class is due to soft refusal.

A residential move also shows different effects for the different classes. For the unimodal classes (strict car and bike) the probabilities do not change much. The other classes are differently affected. The car and bike class show an increase in the probability of becoming a strict car user, while the car and walk class shows a strong increase in the probability of becoming a member of the low mobility or public transport class. One explanation of finding these different effects could be the fact that a residential move is included as a single variable, while it can be expected that the effect of moving from a rural area to an urban area will have a different effect than a move from an urban tot a rural area or move to an area with the same level of urbanization, something that was also shown by Clark et al. (2014) and Prillwitz et al. (2006). It was, however, found that over 85% of the respondents moved to an area with the same level of urbanization, which makes it difficult to explicitly model the effects of a change in the level of urbanization.

After the birth of a child, all classes show an increasing probability of becoming a strict car user. All classes also show an increase in the probability of becoming a member of the car and walk class, in accordance with results found by Scheiner and Holz-Rau (2013). The car and bike class shows a high probability of becoming a car and walk user and vice versa. An increase in car dependency after the birth of a child has also been found in other studies (Fatmi and Habib, 2016; Oakil et al., 2011; Prillwitz et al., 2006) and could be explained because the car is a convenient mode of transport to travel with a baby.

The start or change of education increases the probability of becoming a public transport user for most classes. This is an expected result, since students are provided with a free public transport card in the Netherlands. The low mobility class shows the greatest changes. The probability of remaining in the low mobility class decreases from 69% to only 17%. It should be noted that the group of respondents that started or changed education consists for two-thirds of people under 30 years old, whereas a quarter is over 40 years. This could explain the fact that some students within the sample show low mobility, as this group does not only consist of young people, whom can usually be assumed to be active. Other studies found that changing education leads to a decrease in car availability (Beige and Axhausen, 2008), but no effects on mode choice were found (Scheiner and Holz-Rau, 2013). However, because students are provided with a free public transport card in the Netherlands, it is hard to compare results with studies from other countries.

Overall, it can be observed that the strict car users show very inert behaviour. For all events, except for stop working, the probability of remaining a strict car user after a life event stays similar to the probability when the event does not happen. The bike users, who are also more or less unimodal travellers, show less inert behaviour. This could be explained because a car is usually suitable for all kinds of trips, while a bike is limited due to its speed and lack of possibilities such as taking a baby with you.

5. Conclusions and recommendations

In this paper, latent class- and transition analysis are applied on panel data within the mobility biographies framework to reveal different travel patterns and assess the effect of life events and other exogenous variables on transitions between these travel patterns. Six different meaningful and distinguishable travel patterns were identified. For all life events significant effects on transition probabilities were found. The transition analysis confirms that travel behaviour is inert. In addition, unimodal travellers show a higher probability of remaining in the same travel pattern, compared to multimodal travellers. All identified travel patterns show a very low probability of transitioning towards the public transport travel pattern.

Latent transitions analysis has been shown to provide meaningful insights in the effects of different life events and exogenous variables on changes between travel patterns. Latent transition analysis can be a useful method within the mobility biographies studies as it offers the possibility to account for past travel behaviour when assessing the effect of different life events.

The results offer some interesting insights. After, for instance, the birth of a child a rise in the car dependency is observed, regardless of the initial travel pattern. Apparently, people see the car as one of the few suitable means of transport with a baby. This might indicate that people are not well informed about the possibilities of travelling by bike or public transport with a baby. Future research could assess whether a moment such as birth registration could be used to inform people about other safe possibilities to travel with their child besides car.

It is also observed that, for most classes, public transport use only increases after the start or change of education. A change of jobs, which also reflects students who start their first job after finishing their education, shows a shift towards car use again. Future research could focus on how students could be tempted to remain public transport users, even after they finished their education.

An important drawback of latent transition analysis is the fact that it requires a large sample to reveal significant effects. In this study, the latent transition analysis is used to assess the effect of life events on changes in travel patterns. One of the characteristics of life events is the fact that they do not occur regularly. Since six different travel patterns were identified, the transition matrix consisted of 36 cells (6 initial clusters × 6 future clusters). Because travel behaviour is inert, most people will remain in the same class. The computation of the off-diagonal probabilities is therefore done with a limited number of observations. This is probably the main reason for finding 'only' 72 significant parameters, of which 27 are constants. Of the parameters that indicate the effect exogenous variables and life events, little over 10% are significant. Fortunately, the MPN will be continued the next years. The observed frequency of life events, as well as observed transitions, will therefore grow, increasing the chances of finding significant effects. It is therefore recommended that another latent transition model will be estimated when data from more waves is available.

For a number of life events unexpected results or results that are difficult to interpret are found. One important reason for this is probably the fact that a number of life events have different underlying events. For instance an increase in the number of adults in the household could be because partners started living together, or just because a room in the household was rented out to an adult or a child turned 18. The first event will probably have a larger effect than the others. It is therefore recommended to analyse the effects of life events in more detail. To be able to distinguish more detailed life events, data from more waves are needed. If more data are available, a distinction could be made between, for instance, moving from rural areas to urban areas and vice versa, changing from a full-time to a part-time job and vice versa, stop working due to retirement and due to involuntarily losing a job et cetera.

Another recommendation is aimed at the indicators that are used to define the travel patterns. A limitation of relying on the self-reported trip rates to define the travel patterns is the fact that respondents only reported three days of travel. Since it can be assumed that travel behaviour is different during weekdays compared to the weekend, the data might be biased because travel behaviour has only been reported for three days. Fortunately, respondents were assigned the same starting day every wave and therefore reported the same days every year. Starting from wave 2, respondents are also asked on their weekly frequency of mode use. It is recommended that this will be combined with the self-reported trip rates to get a more accurate overview of their travel behaviour in future research using the MPN data. Since the stated mode use is not available for the first wave, this study could only rely on the self-reported trip rates.

The last recommendation for further research is to include lagged effects to the analysis. It could, for instance, be that after a residential move people change their travel behaviour on the short term, but change this behaviour again on the long term (more than 1 year). Including lagged effects could reveal such behaviour. Modelling lagged effects would require the sample to consist of respondent who participated at least three consecutive waves. Only when data from more waves are available this becomes a viable option.

Appendix A. Parameter estimates of the 6-class transition model

Table 4 shows the parameter estimates of the 6-class transition model.

Table 4
6-Class Transition Parameters.

	Wave 2 class membership					
Wave 1 class membership	Strict car (SC)	Car and bike (CB)	Bike (B)	Car and walk (CW)	Low mobility (LM)	Public transport (PT)
SC						
Constant	0	**−2.25 (0.00)**	**−2.87 (0.03)**	**−2.96 (0.00)**	**−2.46 (0.00)**	**−3.56 (0.00)**
Female (ref. male)	0	**0.44 (0.01)**	0.05 (0.97)	**0.63 (0.03)**	0.31 (0.19)	−0.17 (0.74)
Age (standardized)	0	0.08 (0.54)	−0.73 (0.49)	**0.42 (0.03)**	0.27 (0.11)	−0.30 (0.30)
Age squared	0	−0.11 (0.33)	−0.94 (0.56)	−0.01 (0.93)	−0.05 (0.74)	0.38 (0.15)
Middle educated (ref. low)	0	0.31 (0.22)	−0.26 (0.75)	−0.09 (0.82)	**0.66 (0.05)**	0.00 (1.00)
High educated (ref. low)	0	0.52 (0.05)	−1.49 (0.32)	0.27 (0.50)	0.14 (0.71)	0.53 (0.48)
Sub-urban (ref. urban)	0	0.26 (0.30)	−1.38 (0.33)	0.12 (0.72)	0.25 (0.41)	0.02 (0.97)
Rural (ref. urban)	0	**0.44 (0.04)**	−1.38 (0.25)	−0.54 (0.12)	−0.03 (0.92)	−1.16 (0.15)
Decrease # of adults (ref. = no change)	0	0.08 (0.87)	1.03 (0.50)	0.54 (0.46)	0.01 (0.99)	−2.19 (0.07)
Increase # of adults (ref. = no change)	0	0.18 (0.64)	−1.18 (0.09)	−0.81 (0.51)	0.14 (0.80)	−2.18 (0.28)
New job (ref. = no)	0	0.42 (0.20)	−0.89 (0.12)	0.20 (0.77)	−0.54 (0.45)	0.49 (0.54)
Residential move (ref. = no)	0	0.19 (0.74)	−0.03 (0.97)	0.20 (0.82)	0.05 (0.96)	−0.29 (0.81)
Birth of a child (ref. = no)	0	−0.67 (0.30)	−0.51 (0.51)	**1.14 (0.03)**	−0.23 (0.78)	−0.95 (0.49)
Start/change education (ref. = no)	0	−1.49 (0.13)	−0.68 (0.62)	0.25 (0.82)	−2.17 (0.19)	**1.50 (0.04)**
Stop working (ref. = no)	0	0.73 (0.11)	1.75 (0.14)	−0.63 (0.68)	0.80 (0.14)	0.73 (0.38)
CB						
Constant	**−1.17 (0.00)**	0	**−1.94 (0.00)**	**−2.27 (0.00)**	**−1.86 (0.02)**	**−3.88 (0.00)**
Female (ref. male)	−0.24 (0.23)	0	**0.84 (0.01)**	−0.30 (0.39)	0.39 (0.42)	0.35 (0.59)
Age (standardized)	−0.22 (0.06)	0	−0.03 (0.82)	0.38 (0.18)	−0.32 (0.12)	**−1.04 (0.00)**
Age squared	**0.20 (0.05)**	0	**0.50 (0.00)**	−0.08 (0.71)	0.40 (0.06)	**0.78 (0.00)**
Middle educated (ref. low)	0.39 (0.18)	0	−0.61 (0.08)	0.29 (0.55)	**−1.07 (0.03)**	0.15 (0.80)
High educated (ref. low)	0.12 (0.70)	0	−0.36 (0.29)	0.34 (0.49)	−0.84 (0.18)	−2.09 (0.18)
Sub-urban (ref. urban)	−0.09 (0.71)	0	−0.08 (0.82)	0.38 (0.33)	−0.38 (0.49)	−0.28 (0.71)
Rural (ref. urban)	0.29 (0.22)	0	−0.22 (0.52)	−0.19 (0.70)	−0.86 (0.13)	−0.94 (0.25)
Decrease # of adults (ref. = no change)	−0.58 (0.46)	0	0.00 (1.00)	**−3.88 (0.04)**	−1.45 (0.10)	1.71 (0.07)
Increase # of adults (ref. = no change)	0.09 (0.85)	0	−0.08 (0.89)	−3.30 (0.13)	−0.99 (0.24)	−2.34 (0.06)
New job (ref. = no)	0.40 (0.38)	0	0.31 (0.53)	−0.17 (0.85)	0.07 (0.92)	0.47 (0.62)
Residential move (ref. = no)	0.71 (0.28)	0	0.17 (0.78)	0.57 (0.52)	−1.43 (0.06)	**−3.33 (0.04)**
Birth of a child (ref. = no)	0.68 (0.57)	0	**−2.73 (0.03)**	**2.42 (0.01)**	−0.48 (0.48)	−0.79 (0.42)
Start/change education (ref. = no)	0.93 (0.25)	0	1.04 (0.19)	0.66 (0.63)	**1.78 (0.04)**	1.94 (0.17)
Stop working (ref. = no)	−2.42 (0.38)	0	0.54 (0.49)	1.03 (0.26)	0.20 (0.81)	1.93 (0.06)
B						
Constant	**−2.68 (0.01)**	**−1.79 (0.00)**	0	**−3.47 (0.00)**	−1.51 (0.15)	**−3.76 (0.00)**
Female (ref. male)	−0.56 (0.36)	−0.33 (0.22)	0	0.51 (0.33)	−0.25 (0.56)	0.09 (0.83)
Age (standardized)	−0.22 (0.71)	0.28 (0.08)	0	0.64 (0.10)	−0.81 (0.49)	**−0.65 (0.01)**
Age squared	−0.51 (0.34)	−0.08 (0.58)	0	−0.14 (0.60)	−0.57 (0.56)	0.29 (0.18)
Middle educated (ref. low)	−0.07 (0.92)	0.06 (0.88)	0	0.51 (0.46)	−0.64 (0.40)	0.77 (0.13)
High educated (ref. low)	−0.89 (0.35)	0.39 (0.28)	0	0.66 (0.34)	−1.82 (0.18)	0.92 (0.06)
Sub-urban (ref. urban)	0.12 (0.87)	0.39 (0.26)	0	−0.63 (0.33)	0.20 (0.71)	−0.41 (0.41)
Rural (ref. urban)	0.71 (0.45)	0.23 (0.55)	0	−0.18 (0.78)	−0.05 (0.92)	−0.49 (0.27)
Decrease # of adults (ref. = no change)	−2.69 (0.20)	−1.98 (0.59)	0	−9.26 (0.13)	0.02 (0.98)	0.24 (0.89)
Increase # of adults (ref. = no change)	−0.47 (0.69)	−0.15 (0.81)	0	−0.08 (0.95)	**1.10 (0.04)**	0.30 (0.62)
New job (ref. = no)	2.23 (0.05)	0.24 (0.73)	0	−0.68 (0.74)	0.27 (0.68)	0.63 (0.20)
Residential move (ref. = no)	0.44 (0.68)	0.23 (0.76)	0	−0.65 (0.57)	−0.75 (0.53)	0.36 (0.63)
Birth of a child (ref. = no)	2.17 (0.29)	2.01 (0.36)	0	**4.79 (0.02)**	2.17 (0.35)	−1.95 (0.43)
Start/change education (ref. = no)	0.29 (0.91)	0.73 (0.34)	0	2.37 (0.11)	−4.57 (0.15)	**1.81 (0.01)**
Stop working (ref. = no)	−1.78 (0.33)	−0.67 (0.56)	0	**1.54 (0.04)**	0.63 (0.36)	0.21 (0.79)
CW						
Constant	**−1.50 (0.00)**	−0.07 (0.90)	−1.32 (0.06)	0	**−1.64 (0.03)**	**−2.31 (0.00)**
Female (ref. male)	−0.49 (0.13)	**−1.06 (0.01)**	0.13 (0.77)	0	0.27 (0.59)	−0.09 (0.87)
Age (standardized)	0.31 (0.50)	−0.36 (0.16)	−0.54 (0.06)	0	0.29 (0.46)	**−0.88 (0.03)**

(*continued on next page*)

Table 4 (*continued*)

Wave 1 class membership	Wave 2 class membership: Strict car (SC)	Car and bike (CB)	Bike (B)	Car and walk (CW)	Low mobility (LM)	Public transport (PT)
Age squared	−0.59 (0.12)	**−0.49 (0.04)**	0.03 (0.88)	0	−0.35 (0.14)	0.66 (0.06)
Middle educated (ref. low)	0.58 (0.19)	−0.49 (0.29)	−0.75 (0.18)	0	0.05 (0.91)	−1.19 (0.23)
High educated (ref. low)	0.30 (0.56)	**−1.11 (0.05)**	−0.81 (0.24)	0	−0.90 (0.15)	−0.35 (0.60)
Sub-urban (ref. urban)	0.56 (0.20)	0.20 (0.63)	0.12 (0.80)	0	−0.31 (0.59)	−0.25 (0.76)
Rural (ref. urban)	0.13 (0.76)	−1.15 (0.09)	−1.34 (0.12)	0	−0.71 (0.20)	−1.23 (0.09)
Decrease # of adults (ref. = no change)	0.38 (0.77)	0.37 (0.76)	1.04 (0.27)	0	−3.92 (0.18)	−1.27 (0.48)
Increase # of adults (ref. = no change)	0.14 (0.88)	−5.11 (0.16)	0.87 (0.17)	0	0.18 (0.86)	−2.63 (0.10)
New job (ref. = no)	**1.75 (0.02)**	**1.45 (0.04)**	0.79 (0.32)	0	0.81 (0.41)	−1.03 (0.70)
Residential move (ref. = no)	0.03 (0.99)	1.08 (0.43)	0.75 (0.48)	0	2.28 (0.06)	2.23 (0.15)
Birth of a child (ref. = no)	1.44 (0.45)	2.21 (0.10)	−2.92 (0.09)	0	−2.05 (0.23)	1.41 (0.24)
Start/change education (ref. = no)	−0.68 (0.76)	−0.25 (0.78)	−0.28 (0.79)	0	0.04 (0.98)	−0.19 (0.94)
Stop working (ref. = no)	−2.55 (0.71)	−1.31 (0.40)	−0.14 (0.87)	0	−0.43 (0.66)	−0.09 (0.92)
LM						
Constant	**−2.70 (0.00)**	**−3.15 (0.00)**	**−2.86 (0.00)**	**−3.71 (0.00)**	0	**−5.55 (0.00)**
Female (ref. male)	−0.02 (0.97)	0.35 (0.48)	−0.28 (0.49)	0.32 (0.65)	0	0.52 (0.40)
Age (standardized)	−0.09 (0.64)	0.03 (0.91)	−0.23 (0.25)	0.23 (0.63)	0	−0.38 (0.27)
Age squared	−0.10 (0.64)	−0.08 (0.72)	0.20 (0.25)	0.02 (0.94)	0	0.00 (0.99)
Middle educated (ref. low)	0.71 (0.19)	0.47 (0.47)	0.46 (0.47)	0.22 (0.78)	0	0.79 (0.45)
High educated (ref. low)	0.77 (0.18)	**1.44 (0.03)**	**1.36 (0.02)**	1.09 (0.19)	0	**2.86 (0.01)**
Sub-urban (ref. urban)	0.75 (0.14)	0.29 (0.60)	0.25 (0.65)	0.15 (0.87)	0	0.00 (1.00)
Rural (ref. urban)	0.64 (0.19)	0.13 (0.84)	−0.50 (0.40)	−0.10 (0.92)	0	−0.09 (0.90)
Decrease # of adults (ref. = no change)	−1.75 (0.09)	−0.20 (0.91)	**1.82 (0.04)**	−0.16 (0.92)	0	0.53 (0.63)
Increase # of adults (ref. = no change)	−1.57 (0.16)	−1.22 (0.08)	0.56 (0.50)	0.13 (0.89)	0	1.01 (0.45)
New job (ref. = no)	0.25 (0.79)	−0.62 (0.45)	0.78 (0.25)	−0.65 (0.83)	0	**1.67 (0.05)**
Residential move (ref. = no)	0.66 (0.36)	0.74 (0.51)	0.63 (0.62)	**2.67 (0.02)**	0	−0.07 (0.95)
Birth of a child (ref. = no)	**1.69 (0.01)**	0.56 (0.53)	−0.17 (0.85)	0.63 (0.49)	0	1.16 (0.31)
Start/change education (ref. = no)	2.11 (0.19)	2.58 (0.11)	−0.43 (0.73)	−2.51 (0.34)	0	**4.83 (0.01)**
Stop working (ref. = no)	−0.73 (0.42)	−0.64 (0.50)	−1.53 (0.05)	1.48 (0.13)	0	**−5.22 (0.01)**
PT						
Constant	**−2.13 (0.01)**	**−3.94 (0.00)**	**−3.71 (0.00)**	**−2.62 (0.00)**	**−2.48 (0.00)**	0
Female (ref. male)	0.08 (0.87)	−0.40 (0.64)	**2.35 (0.01)**	0.21 (0.68)	0.63 (0.18)	0
Age (standardized)	0.29 (0.32)	0.34 (0.21)	−0.60 (0.25)	**1.02 (0.00)**	**0.78 (0.01)**	0
Age squared	−0.46 (0.12)	0.25 (0.40)	−0.30 (0.47)	−0.08 (0.70)	−0.18 (0.55)	0
Middle educated (ref. low)	1.24 (0.12)	0.66 (0.42)	−1.97 (0.18)	0.73 (0.35)	0.02 (0.97)	0
High educated (ref. low)	0.39 (0.66)	0.83 (0.34)	−0.13 (0.86)	0.86 (0.22)	−0.05 (0.93)	0
Sub-urban (ref. urban)	0.34 (0.52)	0.43 (0.72)	−0.25 (0.76)	−0.71 (0.37)	0.61 (0.31)	0
Rural (ref. urban)	−0.95 (0.81)	1.09 (0.32)	0.53 (0.50)	0.15 (0.90)	**1.73 (0.01)**	0
Decrease # of adults (ref. = no change)	1.79 (0.08)	1.54 (0.30)	0.77 (0.43)	−1.65 (0.17)	**−4.98 (0.05)**	0
Increase # of adults (ref. = no change)	0.00 (1.00)	−0.17 (0.90)	−1.78 (0.31)	**−3.28 (0.00)**	−0.89 (0.38)	0
New job (ref. = no)	−0.15 (0.95)	1.25 (0.11)	0.41 (0.47)	−0.21 (0.83)	1.32 (0.14)	0
Residential move (ref. = no)	−2.73 (0.16)	1.28 (0.19)	1.93 (0.12)	1.41 (0.30)	**−4.42 (0.00)**	0
Birth of a child (ref. = no)	1.91 (0.23)	−2.03 (0.85)	1.17 (0.28)	2.44 (0.12)	2.04 (0.27)	0
Start/change education (ref. = no)	−0.93 (0.32)	−0.47 (0.75)	−1.92 (0.06)	−2.35 (0.07)	1.37 (0.08)	0
Stop working (ref. = no)	0.07 (0.96)	−1.26 (0.91)	−0.15 (0.84)	1.12 (0.30)	1.17 (0.27)	0

P-values are presented in parentheses, parameters with $p < .05$ are bold.

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