Key events and multimodality: a life course approach

Joachim Scheiner*, Kiron Chatterjee, Eva Heinen

*corresponding author

Prof. Dr. Joachim Scheiner, Technische Universität Dortmund, Faculty of Spatial Planning, Department of Transport Planning, 44227 Dortmund, Germany

phone ++49-231-755-4822, fax ++49-231-755-2269, e-mail joachim.scheiner@tu-dortmund.de

Dr Kiron Chatterjee, Centre for Transport & Society, Department of Geography and Environmental Management, University of the West of England, Bristol BS16 1QY, UK

phone +44(0) 117 32 82032, fax: +44(0) 117 32 83002, e-mail: Kiron.Chatterjee@uwe.ac.uk

Dr Eva Heinen, University of Leeds, Faculty of Environment, Institute for Transport Studies, LS2 9JT Leeds, United Kingdom.

phone +44(0) 113 2431790, e-mail: e.heinen@leeds.ac.uk

Abstract

Since the large majority of households have access to one or more cars in the developed world, encouraging multimodal travel behaviours has become a goal for many cities. Multimodality refers to the use of more than one transport mode within a given period of time. While correlates of multimodality have been identified from cross-sectional data, there is very little known about the circumstances over time in which individuals become more or less multimodal. This paper is the first to fully adopt the mobility biography approach to study changes in multimodality over time at the individual level. Multimodality is measured using four continuous indicators of mode use in a seven-day period: the share in trips made by the most commonly used mode (primary mode), the Herfindahl-Hirschman Index, Shannon's entropy, and the number of modes used. The paper uses the German Mobility Panel (GMP) for the period 1994 to 2012. The results demonstrate that some of the life course events studied are significantly associated with changes in multimodality. Specifically, a child moving out of the household increases the multimodality of parents. Leaving the labour market increases multimodality, while entering the labour market conversely reduces multimodality. Changes in car access and driver licence holding have significant effects as well. An improvement to the public transport system in the neighbourhood increases multimodality, and vice versa. Reduced parking space availability also increases multimodality. The latter two findings endorse 'carrot and stick' transport policies as means of creating a more balanced use of transport modes.

Keywords: multimodality, travel mode choice, mobility biography, life course, key event, travel behaviour change

Key events and multimodality: a life course approach

1 Introduction

Whereas the focus of travel behaviour research has long been on explaining differences in behaviour between individuals (interpersonal variability), there is an increasing interest in intrapersonal behavioural variability (Huff and Hanson, 1986; Chatterjee, 2011; Scheiner and Holz-Rau, 2013; Susilo and Axhausen, 2014; Heinen and Chatterjee, 2015). Intrapersonal variability in this research refers to short-term (day-to-day) variability as well as longer-term variability over the life course. In terms of travel mode use, variability has been considered in the literature using the terms mode choice variability or modal variability (Heinen and Chatterjee, 2015), or multimodality (Kuhnimhof et al., 2012). This is an important development in research, as travel mode choice has for a long time been (and still continues to be) considered in terms of a discrete choice at the trip level. Research on multimodality highlights that individuals may choose to use different modes when their preferences or circumstances vary. Such circumstances may include trip purposes, destinations visited, weather conditions, resources available, or family members involved.

Multimodality has been referred to as the use of more than one transport mode within a given period of time (Kuhnimhof et al., 2012). This definition implies that the prevalence of multimodality increases with the duration of the definition period. The use of more than one mode within a trip is typically referred to as intermodality and can also be considered in the measurement of multimodality. The concept of multimodality is typically applied to individuals, but can also be used for households or population groups. It has been studied in terms of its prevalence, trends over time and its correlates (Heinen and Chatterjee, 2015).

Multimodality has become a growing issue of interest because rising car ownership and use in many parts of the world have led to a range of problems that need addressing by encouraging a more balanced use of different transport options. Encouraging car owners to use alternatives to the car, at least for some of their travel, has become a specific goal for cities in Europe with the 'Do the Right Mix' campaign (EC, 2016). They consider it more realistic to encourage their citizens to make a change to their relative use of different transport modes than to replace the use of one mode with another. Furthermore, it has been shown that multimodal travellers are more inclined to respond to interventions to encourage use of alternatives to the car than individuals with more repetitive mode choices (Heinen and Ogilvie, 2016). These points highlight the practical value of understanding the circumstances in which individuals increase (or decrease) the mix of transport modes they use. Such an understanding will assist with developing effective transport mode change policies.

While correlates (or predictors) of multimodality have been identified from cross-sectional data, there is little known about the circumstances over time in which individuals become more or less multimodal. This can be studied at the individual level using the mobility biographies (or life course) approach. The mobility biographies approach argues that travel behaviour changes are linked to life course events or changes in the urban environment and associated accessibility. Such events and changes may cause mismatch between an individual's situation and his/her behaviour that results in stress, and this stress may trigger short-term or longer-term (lagged) learning and adaptation processes that eventually lead to behaviour change (Clark et al., 2015).

This paper utilises ideas of the mobility biography approach (Müggenburg et al., 2015; Chatterjee and Scheiner, 2015) to study changes in multimodality over time at the individual level. There has been extremely little research on this topic to date (Kroesen, 2014a; Chatterjee et al., in press).

Multimodality is measured using four continuous indicators of mode use in a seven-day period: the share in trips made by the most commonly used mode (primary mode), the Herfindahl-Hirschman Index, Shannon's entropy, and the number of modes used. The paper uses the German Mobility Panel (GMP) for the period 1994 to 2012, in which respondents are asked three times in three consecutive years to complete trip diaries for a week. This is accompanied by personal and household sociodemographic and geographical context information for each of the three survey years which allows reconstruction of life course events based on changes reported in socio-demographics and accessibility. Hence, this paper seeks to: (1) understand travel behaviour change over the life course, with a specific focus on (mid- to longer-term) changes in (short-term) modal variability, (2) contribute to the rare attempts to quantify modal variability using continuous indicators, (3) inform policy makers and practitioners about travel behaviour change and interventions to promote increased multimodality.

The next section reviews research to date on multimodality and longer-term variability in mode use. This is followed by a description of the data, the analysis approach and the variables used. Subsequently the results are presented, including regression models of changes in multimodality over time. The paper finishes with conclusions for further research and policy.

2 State of the research

2.1 Multimodality

In this review we first consider different ways of measuring multimodality before summarising findings on predictors of multimodal behaviour. We identify that there has been very little research investigating the factors that lead to a change in individual-level multimodality over time. Given this gap, we return to transport mode use and summarise what is known about the predictors of a change in transport mode use over time to inform a new analysis of change in multimodality over time.

2.1.1 Measuring multimodality

Multimodality may, broadly speaking, be characterised in two ways. The first way is to classify individuals into nominal categories based on the combination of transport modes they use. Classification can be based on predefined conceptualisation, or determined by the data itself. The second way of characterising multimodality is by quantitative indicators which describe the extent of variability in mode use. The measurement of multimodality is also affected by data available and how it is used. Studies of multimodality have varied in the number of transport mode types considered and in the duration of time over which transport mode use is considered. Information on transport mode use is collected in different ways. Studies have usually used travel diary data, but in some cases asked survey respondents to indicate their typical frequency of using transport modes.

Differences in measurement present difficulties for making comparisons between studies. This is evident from Buehler and Hamre (2015) who estimated from 2009 National Household Travel Survey (NHTS) that 78% of the American population were monomodal car users from one-day travel diary data but only 28% were monomodal car users from respondents' stated frequency of using transport modes over a week. Comparing this with Germany, Nobis (2007) estimated 43% of the German population were solely car users with similar weekly data for Germany in 2002. This implies Americans are more multimodal, but ignores that walking was not considered as a transport mode option by Nobis. For Great Britain an analysis of National Travel Survey data for

2010 showed that an estimated 38% of the British population only used the car in a one-week period with no walking trips or use of other modes (Heinen and Chatterjee, 2015)[1].

2.1.2 Predictors of multimodality

Five recent studies have used multivariate statistical methods (regression or latent class analysis) to identify predictors of multimodality. Two studies used predefined categorisations of multimodality groups (Nobis (2007) with German data, Buehler and Hamre (2015) with data from the United States (US)), two studies used data driven categorisations (Kroesen (2014b) and Molin et al. (2016) for Dutch data) and one study used quantitative indicators of multimodality (Heinen and Chatterjee (2015)). We highlight the more notable findings from these studies but note that caution is necessary when comparing results due to the different data used and analyses performed. The findings below refer to results on predictors after accounting for other factors and not necessarily bivariate relationships.

Multimodality (as opposed to monomodal car use) has generally been found to be more likely for those living in larger urban areas, with better public transport access, younger adults, more highly educated individuals and those living on their own and less likely for those in full-time employment, with greater car availability and with young children in the household.

Being male has been found to be associated with being more multimodal in US, but less multimodal in Great Britain (GB). White ethnicity has been found to be associated with being less multimodal in US but more multimodal in GB. Higher income has been found to be associated with being multimodal in Germany and US, but being a monomodal car user in the Netherlands. In GB and the US, it has been found that multimodality is less likely for older people, while it is more likely in Germany.

2.1.3 Predictors of a change in multimodality

The particular interest in this paper is on understanding why individuals change multimodality over time. We are aware of two studies that have considered this. Kroesen (2014a) used latent class transition analysis to show that individuals who used multiple modes had a higher likelihood of changing from one multimodality group to another compared to those that relied on one mode. Also, younger people were more likely to move between multimodality groups than older people and living in a large city strongly increased the probabilities of transitioning to (or remaining in) the 'public transport user' group. The life events of moving home and changing jobs also increased the likelihood of changing group, indicating that 'these events represent windows of opportunity to accommodate (latent) preferences' (ibid., p. 66).

Chatterjee et al. (in press) investigated transitions in mode use among commuters in Bristol (UK) using data from a panel survey which obtained one week diaries of commuting travel on five occasions at three month intervals. They constructed a three-way grouping of one week commute patterns into 'full car alone', 'partial car alone' and 'no car alone' and found that one in four commuters changed their weekly pattern at the next wave with intermediate changes between groups (e.g. full car alone to partial car alone) more common than extreme changes (e.g. full car alone to no car alone). A transition from full car alone to partial car alone commuting between survey waves was found to be more likely for those with access to a bicycle, a short distance

---

[1] This is higher than the 28% figure found for monomodal car users in the United States, but this may partly be a consequence of the British data being based on full seven day travel diaries, while the American data is based on one-day diaries supplemented with self-reported mode frequencies (with diaries likely to involve under-reporting of walking trips and self-reported responses likely to involve over-reporting of walking trips).

commute, who worked in a different location than usual workplace (during second wave) and who moved home (between waves). The opposite transition was found to be more likely for those with high car parking availability and working part-time. A transition from non-car alone to partial car alone commuting was more likely for those with access to a car, high car parking availability and who worked in a different location than usual workplace. The opposite transition was found to be more likely for older workers and those not working in a different location than usual workplace.

2.2 Predictors of a change in mode use

Given the limited knowledge of predictors of changes in multimodality over time, we briefly review studies of changes in the use of specific transport modes over time to identify what these tell us about determinants of change. Scheiner and Holz-Rau (2013) used German Mobility Panel data for 1994-2008 to analyse year-to-year changes in the number of trips by different transport modes. Significant effects were found for acquiring a driving licence and gaining car availability (increased car driver trips and decreased use of other modes), birth of child (increased walk trips), cohabitating (increased car passenger trips), change in employment status (gaining employment increased car driver trips, losing employment increased walk trips), easier parking at workplace (increased car driver trips), house move to periphery (decreased walk trips) and house move to urban centre (increased walk trips). A follow-up analysis reported gender differences in the effects of life events on mode use (Scheiner, 2014).

Oakil et al. (2011) conducted a multiple regression analysis of the relationship between a range of life events and commute mode changes using data from a retrospective survey capturing 21 year life histories of nearly 200 respondents in the Utrecht region (Netherlands). Switching from commuting by car was associated with changing to part time work, changing employer, and separation from a partner. Switching to commuting by car was associated with birth of the first child, changing employer, and separation from a partner. Clark et al. (2015) quantified the effect of life events on the likelihood of changing commute mode for a large, representative sample of the English working population. Commute mode changes were strongly predicted by changes to distance to work associated with home moved and job changes. High quality public transport links to employment centres were shown to predict switches away from car commuting and mixed land uses shown to predict switches to active commuting. Those with a pro-environmental attitude were more likely to switch away from car commuting than those without such an attitude.

It has also been shown that transport interventions influence commute mode choices. Chatterjee (2011) reported a net increase in bus use after the introduction of a bus rapid transit system in Crawley (UK) with ordered response regression modelling showing the extent to which residents increased bus use was related to the bus travel time reduction they experienced. Thøgersen (2012) showed that a free public transport travel card given to car owning commuters in Copenhagen resulted in an increase in public transport use only for those who had moved home or changed workplace within the last three months.

Heinen et al. (2015) investigated changes in commute mode travel in Cambridge after introduction of a guided busway with a path for walking and cycling in 2011. There was a slight reduction in walking and cycling in 2012 compared to 2009, but multivariate multinomial logistic regression modelling showed that living closer to the new busway predicted an increased likelihood of an increase in share of trips involving walking and cycling mode share and a decrease in share of trips only involving car. With the same data, Heinen and Ogilvie (2016) investigated the extent to which baseline variability in travel mode use was a predictor of future change in mode use. They used three indicators of baseline variability: HHI, the number of different modes used over a week and the proportion of trips made by the main (combination of) mode(s). They found that baseline variability predicted changes in mode use and specifically that commuters with higher baseline variability were more likely to increase their active mode (walking and cycling) share and decrease their car mode share in response to the intervention.

2.3 Existing knowledge and research gaps

While again noting the caution that needs applying in comparing results from different studies, the research across Germany, Great Britain, the Netherlands and the United States has been consistent in finding that multimodal travel behaviour is more likely for those that are younger, not working full-time, without car access, without young children and living in large cities. Different results have been found for age, income and gender. Differences are likely to arise from the different contextual situations in terms of transport provision and base mode share, as well as non-transport factors. The limited studies of changes in individual multimodality over time have found that changes in personal circumstances, in terms of moving home and changing job, increase the likelihood of a change. This is similar to previous findings about change in mode use which highlight the importance of key events, particularly micro-changes in people's lives (life events) but also macro changes in the transport system.

This paper is the first to study intra-individual change in multimodality over time using continuous indicators. The paper contributes to the literature on the travel behaviour-life course relationship which aims to inform policy about travel behaviour change, and it is one of very few contributions that quantify modal variability using continuous indicators. The analysis is somewhat exploratory in nature, as the existing literature is limited and it is difficult to draw firm conclusions on what is to be expected. Nevertheless, we start with the hypotheses that multimodality increases:

1. when social roles, activities and associated trip-making become more diverse (e.g. in adolescence),

2. when resources increase (money, education, time). This favours an increase in multimodality after retirement, after leaving the labour market, and after income increases. On the other hand, the car is a key mobility resource that is likely to limit people's mode use to the car, which may result in decreasing multimodality after an increase in car availability,

3. when the geographical environment allows to do so (e.g. after moving from a rural to an urban area, after improvements in the PT system),

4. when the initial level of multimodality is very low (reflecting tendency for people with extremes in behaviour to move towards less extreme behaviour).

3 Methods

3.1 Data

We use the GMP 1994 to 2012 for our research[2]. The GMP is a trip-diary based household survey with the sample organised in overlapping waves. Every household is surveyed three times over a period of three consecutive years (KIT 2012), e.g. from 1994-1996, before being excluded from the survey. Trips are recorded over a whole week from all household members aged ten years or over. Personal and household-related sociodemographic attributes are collected as well as accessibility and spatial context attributes at the residence and at the household members' places of work or education.

---

[2] The GMP is conducted by the University of Karlsruhe on behalf of the Federal Ministry of Transport and Digital Infrastructure (BMVI). The data are provided for research use by the Clearingstelle Verkehr (www.clearingstelle-verkehr.de).

The GMP has a number of advantages over other data sources that suit our purpose. First, the seven-day record allows us to measure multimodality at the individual level. This is because a week represents a typical temporal unit of organisation in daily life. Second, the GMP is a long-standing panel survey, thus allowing us to study cohort and period effects. Third, and most importantly, the GMP allows us to reconstruct life course events and changes in accessibility from respondents' responses in two consecutive years. Coding life course events from self-reported information may lead to under recording of life events (see Scheiner, 2011, for details). As life course events are relatively rare in an individual's life, when there is uncertainty it is assumed no event occurs. The coefficients estimated are thus based on changes among those for whom it is relatively certain an event occurred, while some of those for whom no event is assumed may in fact have experienced one.

A limitation of the data is that it does not include information about trip stages involving multiple modes. Hence, our analysis is based on the main mode used for a trip. What is more, details of the spatial environment are only collected via respondents' self-reported measures, as there are no geocodes available in GMP. Household income has only been recorded since 2002. We tested effects of income and income change in a sensitivity analysis (see below). Further, no attitudinal information is available in the data.

The data include a total of 30,631 individual weeks of report. For 15,267 weeks complete information is available (including information on change from one year to the next), and these are used in the regression modelling.

3.2 Analysis approach

In previous work using GMP data, cluster-robust regression modelling was used to account for non-independent (clustered) observations arising from repeated observations of the same individuals (Scheiner, 2014). This is not fully satisfactory as there is no determination coefficient available, and the procedure is less efficient than OLS (Wooldridge, 2003). However, the use of OLS regression with non-independent data may result in the underestimation of standard errors because the amount of independent information available is inflated. The significance of parameters may therefore be overestimated (Hedeker et al., 1994). We use a split-half sample method to account for this issue and simultaneously perform a rigorous validation exercise (see below).

As we are interested in change, we calculate change from one year to the next using four continuous outcome variables (normalised Herfindahl-Hirschman Index; mode entropy; number of modes used; share of primary mode in trips, see below). This results in variables distributed symmetrically around zero. Strictly speaking, one of our variables is derived from counts (change in number of modes used), and another is derived from fractional responses (change in share of primary mode), which implies the use of a Poisson model (or negative binomial model in case of overdispersion) and a fractional response model, respectively. However, both change variables are centred around zero rather than exhibiting non-negative values, and both of them show reasonably symmetrical distributions. Hence, we opt for OLS regression for consistency. OLS has been reported to be robust against mild violations of assumptions (Tabachnick and Fidell, 2007).

Given that travel behaviour analysis is typically characterised by high levels of complexity, strong variation and few effects being strong in magnitude, we performed a rigorous validation exercise. There are a maximum of three observations per respondent, i.e. two observations of change (from the first to the second and from the second to the third year of report). We split the sample into two and used one randomly selected observation per respondent to develop the models (main sample). We used the second half as a validation sample.

We also accounted for another source of data clustering which is from observing multiple persons per household whose behaviour may not be independent of each other. We performed a control analysis by randomly selecting only one member of any household (and one observation per individual). The results turned out very similar to the models including all individuals in terms of effect sizes (similarly: Heinen and Chatterjee, 2015). Some effects lost significance, but the level of loss is in line with what one would expect from the decrease in sample size [n enters the calculation of the T statistics in its square root. The resulting reduction in sample size from n=7,656 to n=5,775 reduces T by 13%. This approximately halves the significance level achieved (e.g., from 0.03 to 0.06, or from 0.05 to 0.10)]. Hence, this control analysis did not appear to affect the results substantially. We present the models including multiple household members in this paper.

3.3 Variable definitions

3.3.1 Dependent variables

There are various ways to measure multimodality. It has been common in previous research to use simple categorisations of whether individuals use particular combinations of modes or not. While approaches that classify individuals into distinct multimodality groups enable looking at the combination of modes used, continuous indicators of multimodality enable inter-individual comparisons of the extent of multimodality. Continuous indicators do not identify actual modes used. For instance, a 50-10-10-10-10-10 percent distribution of modes results in the same value of the indicators we use, no matter which mode accounts for 50 percent. However, in our view it is just as important to consider the extent of variability in mode use amongst the population and the factors that influence variability as it is to consider the prevalence of particular modal combinations and how these might be influenced.

Using a travel mode or not is a nominal-scaled variable and, hence, measuring variety in modes used requires a qualitative measure of variance. There are various such measures (Coulter, 1989). Wagner and Franzmann (2000) provide a detailed discussion of three key measures:

1) The variation ratio measures the share of cases (here: trips) that do not fall into the modal category of the distribution. Conversely, the **share in trips made by the most commonly used mode (primary mode)** measures the concentration of trips on one mode. We use this measure but note that it is not a true measure of diversity as it does not address the distribution of trips over other modes.

2) The **Herfindahl-Hirschman Index (HHI)** is a measure of market concentration. It is calculated as the sum of squared values of probabilities, or shares, of all categories (here: modes) considered. As large values reflect strong concentration, the result may be subtracted from one, resulting in an index of diversity (also called index of qualitative variance) (Wagner and Franzmann 2000). HHI emphasises modes with large shares, as it is based on squared values. It ranges from 1/N to one, with N being the number of modes, but can be normalised to range from zero to one (HHI(n), see Formula 2). This normalised form has been used by Heinen and Chatterjee (2015) to study multimodality, and we do so as well.

$$HHI = \sum_{i=1}^{N} {s_i}^2 \qquad (1)$$

$$HHI(n) = \frac{(H - \frac{1}{N})}{(1 - \frac{1}{N})} \qquad (2)$$

3) Another measure of qualitative variance is **Shannon's entropy** that has been developed in information sciences. It describes the amount of heterogeneity in the distribution of modes. As for the measures described above, heterogeneity is minimal when only one mode is used, and reaches its maximum when the total amount (100 percent of trips) is distributed equally over all modes. Similar to HHI, entropy simultaneously considers the number of different modes and the relative amount of modes used. As opposed to HHI, entropy emphasises weakly represented modes rather than primary modes, as it is based on logarithm (Coulter, 1989) (see Formula 3).

$$E = -\sum_{i=1}^{N} (p_i * \ln(p_i)) \qquad (3)$$

In this study the p_i are the shares of modes in trips made in the week of report. Modes not used do not enter the sum. Ultimately, zero entropy means that a person uses only one mode, while the maximum value (ln(N) with N being the number of modes, in our case Max=1.79) means that all modes considered are used with equal shares.

4) Besides, we study the **number of modes used** in a week. This indicator does not consider the frequency of modes used. However, it is an intuitive and easily accessible indicator that has been used in related research (Heinen and Chatterjee, 2015).

All indicators require an appropriate number of mode categories to be used. Heinen and Chatterjee (2015) calculate HHI for eight mode categories and three mode categories. Their models suggest some differences in results between these two measures, but generally show similar results.

We include six modes: walking, cycling, public transport (PT), car driver (including motorcycles), car passenger, and other modes. We assume that a PT user typically does not make a deliberate decision between different PT modes, but uses the mode that best suits the trip under consideration. In some cities (or neighbourhoods) this will be the bus, but in others a light rail or tube system. Walking is excluded in some studies on multimodality (e.g. Kroesen, 2014a), but included here, as it plays a major role in the German transport system, where walking is the main mode in 24 percent of trips (Follmer et al., 2008, 25). We also make a distinction between car driver and car passenger. Car passenger trips account for 15 percent of trips in Germany (Follmer et al., 2008, 25). The modes chosen also make sure that all categories are represented in the data to a reasonable extent. As we are interested in change, we calculate change from one year to the next from the four variables discussed. This results in continuous outcome variables distributed symmetrically around zero.

3.3.2 Explanatory variables

Travel behaviour change when considered in a life course perspective theoretically depends on change in socio-demographic or space-time circumstances (key events) or preferences, and on previous behaviour (path dependency). Change may also be more likely in certain circumstances than in others without any key event due to social influences and processes, because some life situations permit or encourage variation more than others, and because some life stages have stronger links to rapid development than others (e.g., adolescence). Based on previous work (Scheiner 2014, Scheiner and Holz-Rau 2013) we started by including a large range of explanatory variables reflecting socio-demographics and spatial context at the residence and at the place of work or education (for the sake of brevity: workplace) in the modelling. This included state variables as well as change variables that reflect life course events or changes in spatial context, mobility resources and accessibility. Variables that did not pass a very moderate significance level of p=0.10 in any model were excluded in a stepwise process. As women have been found to adapt in more flexible ways to changing circumstances than men (Polk, 2004; Yun et al., 2011), we also tested interaction terms of key events and socio-demographics with gender. The following variables were tested, but excluded:

Socio-demographic state variables: Living with partner (yes/no), birth cohort, period (year of survey), and household equivalent income were fully excluded. Income was not close to reaching statistical significance, nor a notable magnitude of coefficient. Occupation categories were reduced to only one. Neither part-time nor unemployed were significantly or markedly (in terms of magnitude) different from full-time in any model. Hence, full-time, part-time and unemployed were put into one reference category, while a dummy capturing apprenticeship/trainee/student was retained in the models.

Spatial / accessibility state variables: City size category, central versus remote location of residence (self-report), urbanity (calculated from self-reported walking access from home to various facilities), walking distance from PT stop to workplace.

Socio-demographic change variables (key events): Birth of a child, household foundation with partner, separation from partner, finished school or apprenticeship, start of apprenticeship, change in workplace, income change.

Spatial / accessibility change variables: PT connection to workplace gets worse or better (calculated from self-report about connection quality), change in residential location (upward versus downward in the central place hierarchy), change in urbanity.

Note that the exclusion of these variables does not necessarily mean that they do not influence changes in multimodality, as they may be closely associated with other variables retained in the model. For instance, it is very likely that residential relocation and the associated changes in urbanity influence multimodality, but this association is captured by the variable 'change in PT quality in the neighbourhood' which represents urbanity to some extent.

Also, most interaction terms with gender were excluded over the course of the modelling. In one case an interaction effect was excluded in this procedure that had been significant in an earlier modelling stage. The interaction between entry into the labour market and gender suggested that men, but not women, reduce multimodality when entering the labour market. The significance could not be reproduced when the models were developed further. For the variables that were retained in the models see Table 1 and Table 2 for an overview of descriptive statistics.

Note that some variables may reflect contrasting circumstances. For instance, PT quality in the residential neighbourhood may change due to a relocation or due to a change in (the evaluation of) the PT system. Similarly, the parking situation at the place of work may change due to workplace change, or due to a change in parking regulations or land-use at a given workplace.

		Mean	SD	Min	Max
Dependent variables					
Change in...					
... no. of modes	C	-0.032	1.03	-4	4
... mode entropy	C	-0.009	0.36	-1.41	1.47
... HHI, normalised	C	0.006	0.23	-0.89	0.87
... share of primary mode	C	0.005	0.19	-0.71	0.67
Explanatory variables					
No. of children in household (< 10 yrs)	B	0.24	0.59	0	4
No. of children in household (10-13 yrs)	B	0.14	0.41	0	3
No. of children in household (14-17 yrs)	B	0.15	0.42	0	3
PT quality in neighbourhood (variety of different	B	2.46	1.07	0	5

systems accessible on foot, self-report)					
Change in PT quality in neighbourhood	C	0.02	0.71	-3	3
Baseline no. of modes	B	2.77	0.98	1	6
Baseline mode entropy	B	0.72	0.37	0	1.63
Baseline HHI, normalised	B	0.58	0.26	0.09	1
Baseline share of primary mode	B	0.68	0.19	0.24	1
n (main sample)			7,656		

Table 1: Continuous variables used in regression: descriptive statistics

B = baseline variable; C = change variable.

			Baseline...			
		Per cent 'yes'	No. of modes	Mode entropy	HHI, normal-ised	Share of primary mode
Gender female	B	51.9%	2.82*	0.76*	0.55*	0.66*
Gender male	B	48.1%	2.68*	0.67*	0.59*	0.71*
Age group						
10-17 years	B	6.9%	2.98*	0.86*	0.40*	0.59*
18-29 years (Reference)	B	9.1%	3.02*	0.80*	0.57*	0.65*
30-44 years	B	25.5%	2.81*	0.70*	0.62*	0.70*
45-59 years	B	26.3%	2.67*	0.66*	0.62*	0.71*
60-74 years	B	27.4%	2.66*	0.71*	0.54*	0.67*
75+ years	B	4.7%	2.48*	0.65*	0.56*	0.70*
Child(ren) in household (< 10 yrs)^	B	17.7%	2.89*	0.74*	0.58	0.68
Child(ren) in household (10-13 yrs)^	B	13.3%	2.94*	0.79*	0.51*	0.64*
Child(ren) in household (14-17 yrs)^	B	14.2%	2.88*	0.76*	0.54*	0.66*
No children in household^	B	66.3%	2.70*	0.70*	0.58*	0.69*
Apprenticeship, trainee, education	B	12.0%	3.05*	0.85*	0.45*	0.60*
Education level						
Elementary school qualification without apprenticeship or no qualification	B	11.9%	2.82*	0.79*	0.47*	0.63*
Elementary school qualification plus apprenticeship	B	24.6%	2.56*	0.64*	0.62*	0.72*
Secondary school qualification level I	B	28.3%	2.74*	0.71*	0.60*	0.69*
University entrance qualification or higher (Reference)	B	35.1%	2.90*	0.75*	0.56*	0.67*
PT quality in neighbourhood poor (0-2 systems)^	B	54.3%	2.70*	0.69*	0.61*	0.70*
PT quality in neighbourhood good (3+ systems)^	B	45.7%	2.83*	0.75*	0.53*	0.66*
PT connection to place of work or education						
Good connection (fast direct connection or max. one change) (Reference)	B	65.2%	3.01*	0.81*	0.50*	0.64*
Poor connection (> 1 change, or slow direct connection)	B	18.8%	2.79*	0.69*	0.62*	0.70*
No connection	B	16.0%	2.63*	0.64*	0.66*	0.73*
Parking situation at workplace is difficult or very difficult	B	14.5%	3.01*	0.80*	0.51*	0.64*
Parking situation at workplace is not difficult	B	85.5%	2.71*	0.70*	0.58*	0.69*
Driving licence holding	B	83.1%	2.79*	0.71*	0.60*	0.69*
No driving licence	B	16.9%	2.62*	0.72*	0.49*	0.66*
Driving licence holding * female	B	41.0%	2.91*	0.77*	0.58*	0.66*
Car availability						

No car available (Reference)	B	26.9%	2.69*	0.72*	0.51*	0.67*
Occasionally / after agreement	B	11.7%	3.19*	0.89*	0.50*	0.60*
Car regularly available	B	61.4%	2.72*	0.67*	0.64*	0.71*
Child moving out	C	2.0%	2.96*	0.79*	0.55	0.66
Entry into labour market	C	3.7%	2.86*	0.75	0.57	0.66
Leaving labour market (no retirement)	C	2.1%	2.77	0.73	0.58*	0.68
Retirement	C	3.0%	2.51*	0.68	0.58	0.69
Parking situation at workplace gets much worse (two- or more-point decline on a four-point scale)	C	1.6%	2.92*	0.74*	0.58*	0.67*
Parking situation at workplace gets much better (two- or more-point improvement on a four-point scale)	C	1.9%	2.85*	0.73*	0.57*	0.68*
Loss of driving licence	C	1.1%	2.45	0.63	0.60*	0.71
Achievement of driving licence	C	2.1%	2.75	0.75	0.50*	0.65
Loss in car availability	C	5.8%	2.91*	0.76*	0.56*	0.66*
Increase in car availability	C	6.0%	2.97*	0.79*	0.55*	0.65*
Total sample		100.0%	2.76	0.72	0.57	0.68
n (main sample)		7,656				

Table 2: Dummy variables used in regression: descriptive statistics and baseline multimodality values for population groups

All variables are coded as yes=1, no=0.
B = baseline variable; C = change variable.
^ Dummy variables, used as continuous variables in regression.
* Difference between groups significant (p=0.05, t-Test or F-Test, in case of multiple categories). All change variables tested against "no change".

4 Results

4.1 Correlations between different multimodality indicators and between multimodality and mode use

We begin the results presentation with a brief discussion of cross-sectional correlations between the indicators to point out to which extent the indicators represent different dimensions. We also look at correlations between the indicators and the underlying mode shares to illustrate the links between multimodality and modes used (Table 3).

The four indicators of multimodality are strongly correlated with each other, with correlations ranging between $|r|=0.59$ and 0.90. As expected, the two indicators that reflect levels of modal concentration (HHI and the share of primary mode) are negatively correlated to the indicators that reflect variability (number of modes and mode entropy). The entropy measure shows the strongest correlations with other measures (all $|r|>0.80$) while all other indicators show at least one correlation of medium strength ($|r|<0.60$). We conclude that the measures emphasise different subtleties of multimodality, while all of them roughly reflect the same dimension of travel behaviour, i.e. multimodality.

The multimodality indicators are moderately to weakly correlated to mode shares. The strongest correlations appear between multimodality and the share of trips made as a car driver (correlations ranging between $|r|=0.31$ and 0.49), which is negatively correlated with multimodality and positively with modal concentration. Correlations with all other modes are in the opposite direction, and they are weaker than those between multimodality and driving (correlations ranging between $|r|=0.06$ and 0.36). The strongest correlations – besides driving – can be seen with walking. These results suggest that more multimodality is typically associated with lower levels of driving, and vice versa. Driving is also the mode that shows the strongest negative correlations with all other modes. All directions of correlations are consistent with Heinen and Chatterjee (2015).

	Multimodality indicators			Mode shares					
	Mode entropy	HHI, normalised	Share of primary mode	Car driver	Car passenger	Public transport	Cycling	Walking	Other modes
Multimodality									
No. of modes	.840	-.597	-.590	-.309	.118	.100	.060	.114	.089
Mode entropy		-.819	-.900	-.474	.197	.119	.067	.219	.079
HHI, normalised			.815	.479	.043	-.173	-.136	-.358	-.075
Share of primary mode				.486	-.202	-.105	-.056	-.252	-.061
Mode shares									
Car driver					-.424	-.232	-.251	-.393	-.080
Car passenger						-.151	-.163	-.202	-.010*
Public transport							-.168	-.196	-.011*
Bicycle								-.221	-.026^
Walking									-.054

Table 3: Correlations between various multimodality indicators and mode shares

Pearson correlations. All correlations are significant (p=0.01), except for ^ (p=0.05) and * (p>0.05). n=8,008 (main sample).

4.2 Baseline levels of multimodality

Table 2 reports mean baseline values for the four multimodality indicators for various population groups. We briefly summarise key results.

All four indicators show that women are more multimodal than men. The indicators show less consistent differences between age groups. The number of modes used declines from one age group to the next. The share of the primary mode increases in young adult age and remains at about the same level in older age. It is somewhat lower among the 60-74 age group. This is reflected in entropy, which shows an inverse trend. HHI shows similar age trends, but remains low in old age. Having children is associated with more multimodality. This is most pronounced for those with children in the age bracket 10-13 years.

Those in education (students, trainees) have higher multimodality levels than those who are employed, unemployed or retired. Multimodality levels increase with education level. As an exception, those with the lowest level exhibit high levels of multimodality as well. This is due to school students in this group.

A good PT connection on the commute is associated with considerably more multimodality. The same is true for those with difficult parking situation at the workplace and for living in a neighbourhood with a well-developed PT system, although the latter shows more moderate differences.

Respondents without a driving licence use fewer modes, but also have lower levels of HHI, implying more variability in mode use, than those with a licence. These respondents are mainly adolescents and elderly women. Specifically, women with a driving licence have higher levels of multimodality than the average respondent, particularly in terms of the number of modes used. With respect to car availability, those having occasional car access are most multimodal. Those with permanent car access are least multimodal. The number of modes used is an exception to this statement, as those without car access use slightly fewer modes than those with permanent access to a car.

Turning our attention to change variables, parents with a child who will move out (by the following survey wave) are somewhat more multimodal than the average respondent, especially with respect to the number of modes used. The same is true for those who will enter the labour market in the following year. The opposite is true for those who will retire.

Those who will experience the parking situation at their workplace getting much worse use an above-average number of modes. Interestingly, the same is true (albeit to a lesser extent) for those who will experience the parking situation at their workplace getting much better.

Those who will lose their driving licence show a low baseline level in multimodality, particularly with respect to number of modes and entropy (not significant). Those who will experience changes in car availability have high baseline levels of multimodality, again particularly with respect to number of modes and entropy. This is true for both directions of change (decrease or increase in car availability). The reason is probably that change typically starts from occasional availability of a car, i.e. from the group that exhibits very high levels of multimodality (see above).

These findings (from simple descriptive analysis) are generally consistent with findings reported from previous studies (mostly multivariate analysis, see Section 2.3). Multimodality changes from one year to the next should be seen against the baseline context of different levels of multimodality among population groups and urban settings.

4.3 Correlations between multimodality in two consecutive years

In order to illustrate the amount of change in multimodality from one year to the next, Table 4 presents correlations between levels of multimodality in two consecutive years, as well as between baseline levels of multimodality and change. All correlations are strongly significant, and they vary between r=0.44 and r=0.61, which suggests strong robustness in behaviour over time. On the other hand, the correlations are not such that a 'deterministic' habit can be concluded.

The correlations between baseline behaviour and behavioural change are significantly negative, ranging between r=-0.43 and r=-0.52, indicating the well-known phenomenon of ‘regression to the mean’. Individuals with extreme behaviour tend to move towards more average behaviour (i.e. those with very high levels of multimodality tend to reduce their multimodal behaviour, and vice versa).

	Correlation between baseline behaviour and...	
	...follow-up year	...behavioural change
No. of modes	0.444	-0.519
Mode entropy	0.537	-0.475
HHI, normalised	0.619	-0.428
Share of primary mode	0.526	-0.485

Table 4: Correlations between baseline and follow-up year multimodality, and multimodality change

Pearson correlations. All correlations are significant (p<0.005). n=8,008 (main sample).

4.4 Multiple regression analysis of change in multimodality

4.3.1 Baseline variables

Gender is not statistically significant in any model. It should however be noted that gender is associated with an increase in multimodality when the gender interaction with having a driving licence is excluded from the models.

Adolescents increase their multimodality more than those aged 18-29 years (Model 1, in all other models the effect just fails to reach significance, but is significant in the validation sample). This is in line with expectations, as teenage years are associated with an increasing range of activity spaces and associated mode options. The age bracket 60-74 years is also associated with a disproportional increase in multimodality (Models 3 and 4, Model 2 validation sample). This is probably connected with retirement. We found retirement to be significantly associated with an increase in multimodality when age was not included, but ultimately opted for the models that include age groups as these appeared to capture change better. Similarly, finishing school or apprenticeship is associated marginally with an increase in multimodality when age groups are not included. Hence, age and key events strongly interact in some cases.

Interestingly, old age is associated with a disproportionately large decrease in multimodality in Model 1, suggesting that the elderly may tend to limit their travel to fewer modes that fit their needs or skills best. However, Model 3 shows a negative effect of old age on HHI change in the validation sample, suggesting an increase in multimodality. Hence, changes in older age are not fully clear.

Having children is associated with an increase in multimodality (Model 1 and 2), but the effect is significant for both samples only with respect to the number of modes used (Model 1), and children younger than ten.

Being in education is the only one of four occupation categories that is significantly different from the other categories (Models 2, 3, and 4), but only in the validation sample. Trainees and students typically have low incomes, and use cars less than those employed. We suspect that this is particularly true for university students who often have PT semester tickets and tend to cycle in Germany. Notably, being unemployed did not turn out significantly different from being employed in any model and was thus excluded from the models presented here.

Education level consistently shows increases in multimodality are stronger for those with a university entrance qualification or higher education level compared to those with a lower education level, although these associations are only simultaneously all significant in Model 1 (plus Models 2 and 3 in the validation sample).

A number of accessibility-related variables are consistently associated with changes in multimodality across the models. Firstly, a good PT connection on the commute, relative to a poor or missing connection, is associated with an increase in multimodality (all models). Secondly, the same is true for a difficult parking situation at work (all models). Thirdly, high quality PT in the residential environment is also associated with an increase in multimodality (all models). While these three results indicate urban environments facilitate increased multimodality, it is notable that urbanity in terms of neighbourhood access to facilities did not exhibit any significant associations and was therefore excluded from the models. This suggests that multimodality is more linked to the transport system than to land use, although it must be acknowledged that the transport system is itself highly determined by land use.

Two other variables reflect individual mobility resources. Holding a driving licence is associated with an increase in multimodality for women, but not for men (Models 2 and 4, and Model 1 validation sample). Car availability shows interesting effects that confirm the descriptive results above. While having a car available 'occasionally or after agreement' (as stated in the questionnaire) is associated with an increase in multimodality (Models 1, 2, and 4), regular car availability is associated with a decrease in multimodality (Model 3, Model 4 main sample, Model

2 just fails to reach significance in the main sample). The latter is in line with the expectation that car owners typically limit their travel to using the car, and the former is likely to reflect that those who have a car available, but not all the time, use a mix of various modes (including driving and being a car passenger), while those who have no car available have more limited options.

Lastly, baseline behaviour is not only the strongest baseline variable, but also the dominating effect on multimodality change overall (all models). The more somebody's baseline behaviour is limited to few modes, the more this person increases the number of modes they use, and vice versa (see Section 4.2). This indicates that behavioural extremes are likely to converge towards the mean over time, as has been found for mode use (Scheiner, 2014; Klinger and Lanzendorf, 2016) and car ownership (Cao et al., 2007).

4.3.2 Change variables

Travel behaviour has frequently been found to depend more on people's individual life situations than on space-time context (Stead et al., 2000; Cao et al., 2007; Etminani-Ghasrodashti and Ardeshiri, 2015). However, the above results suggest that geographical context is at least as important for behavioural change as sociodemographic situation, and this is also true when we look at change variables.

Among the life course events studied, few are significant. Firstly, a child moving out of the parental household is associated with an increase in parents' multimodality (Models 2 and 3, Model 4 main sample, Model 1 validation sample). This may reflect more liberty of parents with mode choice when released from escort commitments and other parental responsibilities. Travel behaviour of those living with children is known to be more constrained (Schwanen et al., 2008) and car-dependent (Scheiner and Holz-Rau, 2007) than that of others. In numerical terms, an individual living in a household where a child moves out is predicted to increase the number of modes used by 0.08, and reduce the share of their primary mode by 4% (0.04) on average.

Secondly, entry into the labour market is associated with a decrease in multimodality (Models 3 and 4, Model 2 validation sample; Model 1 just fails to reach significance in the validation sample). Conversely, leaving the labour market is associated with an increase in multimodality (all models, but no significant effects in the validation sample). These two findings taken together seem to reflect the well-known car-dependent mobility of those in the labour market. Even the travel behaviour of those who do not commute by car is likely to rely on few modes, particularly the commute mode.

Thirdly, this interpretation is further supported by the results for retirement. Retirement is significant in just one model (Model 3, validation sample) and just fails to reach significance in another model (Model 2, validation sample). Even though this is clearly not satisfactory stand-alone evidence, both results suggest an increase in multimodality on retirement.

Other significant change variables relate to accessibility and mobility resources. A key variable here is a positive change in PT quality in the neighbourhood, which is associated with an increase in multimodality (all models, but only Model 3 in the validation sample). According to the models, the predicted number of modes used increases by 0.03, while the share of the primary mode decreases by 1% with any additional PT system available in the neighbourhood. Respondents reporting that the parking situation at their workplace got much worse are likely to increase their multimodality (Model 2, and Model 3), and vice versa (Model 3, and Model 1).

An increase in car availability (from no car to having a car available, or from occasional to regular availability) is associated with a decrease in multimodality (Models 3 and 4, Model 2 validation sample), presumably because these respondents tend to limit their mode choice to the car. Conversely, a loss in car availability is associated with an increase in multimodality (all models).

Gaining a driving licence is associated with a smaller effect than increasing car availability, but also increases the number of modes used in Model 1 (both samples). This confirms the expectation that young people getting licenced will initially expand their choices, as a new option (driving) becomes available to them, while in the longer run they may start to limit their travel to the car. This interpretation is further supported by the relatively low baseline level of multimodality among those with permanent car access (Section 4.1).

		Change in...															
		No. of modes (Model 1)				Mode entropy (Model 2)				HHI, normalised (Model 3)				Share of primary mode (Model 4)			
		B	SE	Beta	Sig.	B	SE	Beta	Sig.	B	SE	Beta	Sig.	B	SE	Beta	Sig.
Gender female	B	0.04	0.05	0.02	0.42	0.01	0.02	0.01	0.75	0.00	0.01	0.00	0.92	0.00	0.01	0.00	1.00
Age group (ref.: 18-29 years)																	
10-17 years	B	0.17	0.08	0.04	0.03	0.05	0.03	0.04	0.07	-0.03	0.02	-0.04	0.08	-0.03	0.01	-0.04	0.06
30-44 years	B	0.00	0.05	0.00	0.94	0.00	0.02	0.00	0.92	-0.02	0.01	-0.04	0.05	0.00	0.01	0.00	0.88
45-59 years	B	-0.04	0.05	-0.02	0.40	-0.01	0.02	-0.01	0.70	-0.02	0.01	-0.04	0.05	0.00	0.01	0.00	1.00
60-74 years	B	0.00	0.05	0.00	0.96	0.02	0.02	0.03	0.18	-0.05	0.01	-0.09	<0.005	-0.02	0.01	-0.04	0.05
75+ years	B	-0.18	0.07	-0.03	0.01	-0.04	0.02	-0.02	0.10	-0.01	0.02	-0.01	0.58	0.01	0.01	0.02	0.27
No. of children in household (< 10 yrs)	B	0.07	0.02	0.04	<0.005	0.02	0.01	0.03	0.02	-0.01	0.00	-0.01	0.25	0.00	0.00	-0.01	0.42
No. of children in household (10-13 yrs)	B	0.04	0.03	0.01	0.19	0.00	0.01	0.00	0.82	-0.01	0.01	-0.01	0.44	0.00	0.01	0.00	0.80
No. of children in household (14-17 yrs)	B	0.06	0.03	0.03	0.02	0.01	0.01	0.01	0.20	0.00	0.01	0.01	0.45	0.00	0.01	0.00	0.92
Apprenticeship, trainee, education	B	0.09	0.06	0.03	0.15	0.03	0.02	0.03	0.16	-0.02	0.01	-0.03	0.11	-0.01	0.01	-0.02	0.36
Education level (ref.: university entrance qualification or higher)																	
Elementary school qualification...																	
...without apprenticeship or no qualification	B	-0.12	0.05	-0.04	0.01	-0.02	0.02	-0.02	0.25	0.01	0.01	0.02	0.33	0.01	0.01	0.01	0.43
...plus apprenticeship	B	-0.13	0.03	-0.05	<0.005	-0.03	0.01	-0.03	0.01	0.02	0.01	0.04	<0.005	0.01	0.00	0.03	0.02
Secondary school qualification level I	B	-0.07	0.03	-0.03	<0.005	-0.01	0.01	-0.02	0.11	0.01	0.01	0.02	0.04	0.01	0.00	0.01	0.27
PT connection to workplace (reference: good)																	
No connection	B	-0.13	0.03	-0.05	<0.005	-0.05	0.01	-0.05	<0.005	0.04	0.01	0.06	<0.005	0.03	0.01	0.05	<0.005
Poor connection	B	-0.10	0.03	-0.04	<0.005	-0.04	0.01	-0.05	<0.005	0.04	0.01	0.06	<0.005	0.02	0.01	0.05	<0.005
Parking situation at workplace (very) difficult	B	0.12	0.03	0.04	<0.005	0.04	0.01	0.04	<0.005	-0.03	0.01	-0.04	<0.005	-0.02	0.01	-0.03	<0.005
PT quality in neighbourhood (variety of different systems accessible on foot)	B	0.06	0.01	0.06	<0.005	0.02	0.00	0.07	<0.005	-0.02	0.00	-0.08	<0.005	-0.01	0.00	-0.06	<0.005
Driving licence holding	B	0.10	0.06	0.04	0.09	0.01	0.02	0.01	0.67	0.01	0.01	0.01	0.68	0.00	0.01	0.00	0.97
Driving licence holding * female	B	0.08	0.06	0.04	0.17	0.05	0.02	0.07	0.02	-0.01	0.01	-0.03	0.36	-0.03	0.01	-0.07	0.01
Car availability (reference: no)																	

Occasionally / after agreement	B	0.17	0.04	0.05	<0.005	0.06	0.01	0.05	<0.005	-0.02	0.01	-0.02	0.07	-0.03	0.01	-0.05	<0.005
Regularly	B	0.00	0.03	0.00	1.00	-0.02	0.01	-0.03	0.06	0.04	0.01	0.09	<0.005	0.02	0.01	0.05	<0.005
Baseline behaviour	B	-0.60	0.01	-0.57	<0.005	-0.51	0.01	-0.53	<0.005	-0.44	0.01	-0.50	<0.005	-0.52	0.01	-0.54	<0.005
Child moving out	C	0.08	0.08	0.01	0.32	0.06	0.03	0.02	0.03	-0.04	0.02	-0.02	0.03	-0.04	0.01	-0.03	<0.005
Entry into labour market	C	-0.01	0.06	0.00	0.93	-0.03	0.02	-0.02	0.12	0.04	0.01	0.03	<0.005	0.02	0.01	0.02	0.03
Leaving labour market (no retirement)	C	0.15	0.07	0.02	0.04	0.08	0.02	0.03	<0.005	-0.04	0.02	-0.03	0.01	-0.04	0.01	-0.03	<0.005
Retirement	C	0.09	0.06	0.01	0.16	0.00	0.02	0.00	0.87	0.00	0.01	0.00	0.81	0.01	0.01	0.01	0.37
Parking situation at workplace gets much worse	C	0.09	0.07	0.01	0.22	0.05	0.03	0.02	0.06	-0.04	0.02	-0.02	0.03	-0.02	0.01	-0.01	0.16
Parking situation at workplace gets much better	C	-0.17	0.08	-0.02	0.03	-0.04	0.03	-0.01	0.17	0.03	0.02	0.02	0.07	0.01	0.01	0.01	0.43
Change in PT quality in neighbourhood	C	0.03	0.01	0.02	0.05	0.01	0.01	0.03	0.01	-0.01	0.00	-0.03	<0.005	-0.01	0.00	-0.03	<0.005
Loss of driving licence	C	-0.08	0.09	-0.01	0.41	-0.02	0.03	-0.01	0.47	0.01	0.02	0.00	0.75	0.02	0.02	0.01	0.38
Achievement of driving licence	C	0.22	0.08	0.03	0.01	0.05	0.03	0.02	0.07	0.02	0.02	0.01	0.30	-0.02	0.01	-0.01	0.25
Loss in car availability	C	0.11	0.04	0.03	0.01	0.05	0.02	0.03	<0.005	-0.03	0.01	-0.03	0.01	-0.03	0.01	-0.03	<0.005
Increase in car availability	C	-0.02	0.05	0.00	0.71	-0.03	0.02	-0.02	0.07	0.04	0.01	0.04	<0.005	0.02	0.01	0.03	0.01
Intercept		1.36	0.08		<0.005	0.29	0.03		<0.005	0.28	0.02		<0.005	0.38	0.02		<0.005
R^2 adj		0.295				0.251				0.215				0.259			
N		7,656				7,656				7,656				7,656			

Table 5: Regression models of changes multimodality

B = baseline variable; C = change variable. SE=Standard error

5 Conclusions

This paper is one of the earliest to study the effects of life course events and access changes on changes in multimodality. Increasing the number of modes that individuals are prepared to use has become a goal for cities in Europe with the ‘Do the Right Mix’ campaign (EC, 2016), and understanding the circumstances in which individuals increase (or decrease) the mix of transport modes can assist with developing effective transport mode change policies to achieve this.

Some of the key events studied are significantly associated with changes in multimodality. Specifically, a child moving out releases parents from family constraints and increases their multimodality. The same is true for leaving the labour market, while entering the labour market conversely tends to limit people's travel to fewer modes. These observations are in line with our hypothesis 2, which states that multimodality increases when (temporal) resources increase. Changes in car access and driver licence holding have significant effects. Licence *holding* seems to make a difference for women in terms of multimodality, but not for men. Adolescents increase their levels of multimodality more than other age groups, which is in line with hypothesis 1. One might also expect changes in multimodality as an outcome of other social role changes, e.g. after the birth of a child, but we find no evidence on this.

While it has been proposed that people's socio-demographic life situation is more important for travel behaviour than geographical context (Stead et al., 2000; Cao et al., 2007; Etminani-Ghasrodashti and Ardeshiri, 2015), we note that – in line with hypothesis 3 – an urban environment increases multimodality, while only few socio-demographic life events exhibit significant associations. The quality of the PT system in the residential neighbourhood, measured here in terms of a hierarchically structured system composed of different modes that serve different needs from local to regional travel, shows particularly consistent positive effects on multimodality. Reduction in parking spaces also increases multimodality.

However, some life course changes may manifest themselves not through key events but through more gradual processes over time that are reflected by life stages such as adolescence and older age. Consistently, it is found that increases in multimodality are stronger for those with higher education. It is not certain why this is the case, but it might be due to greater previous experience of using different transport modes and greater need to be flexible about travel behaviour.

The strongest effects of all are from baseline behaviour, confirming our hypothesis 4. Path dependence is a phenomenon well known in travel behaviour studies (Cao et al., 2007; Scheiner, 2014; Klinger and Lanzendorf, 2016). The strong negative effects found here indicate that behavioural extremes are likely to converge towards the mean over time.

While previous studies reported increasing multimodality over time in the aggregate (Kuhnimhof et al., 2012, Buehler and Hamre, 2015), we do not find significant period effects.

A number of recommendations can be drawn for further research. Firstly, there are multiple ways to measure multimodality. The variations between the models presented here suggest that results depend on the indicator chosen, which is in line with Heinen and Chatterjee (2015). This is also supported by the finding that some correlations between indicators are only moderate. However, we also note that there is little obvious contradiction between the indicators chosen. Each indicator has its own pros and cons. For research purposes it may be appropriate to opt in favour of more complex measures that take into account as much information as possible on an individual's modal pattern, while for a policy study it may be appropriate to choose a more intuitive measure such as the number of modes used.

Other studies (such as Kroesen (2014a)) have used group membership rather than continuous variables to study multimodality. The shortcoming of this approach is that behaviour may gradually change over time, and the subtleties of change may not be captured by changes in group membership. Also, change in group membership does not imply change in variability. On the other hand, group membership allows direct consideration of the specific modes used, while our study does not allow this. This may also be the reason for the lack of statistically significant effects in some cases. For example, unemployed and full-time employed were not identified as significantly different statistically in our analysis, and the reason may be that both groups are limited in mode variability to the same extent, but to different modes.

Secondly, Müggenburg et al. (2015) suggest that more emphasis in mobility biographies research should be placed on employment-related events, and our results support this idea. Multimodality seems to be more related to employment changes than to family events.

Thirdly, the age effects we found suggest focusing on longer-term processes in behavioural change rather than looking at discrete key events. Also, effects of other baseline state variables such as the number of children in a family, education level and car availability suggest that people constantly adjust their modal behaviour over time rather than instantly reacting to key events and maintaining a certain state of behaviour in periods without key events. This also suggests that the mobility biographies approach should adopt a more process-oriented perspective in order to attain a richer understanding of long-term changes in travel, rather than limiting themselves to pre-defined life course stages. In terms of methodology this may be achieved by placing more emphasis on people's self-reflexive narratives of their own biography instead of (only) working with pre-defined categories of stages and transitions (Miles et al., 2013; Jones et al., 2014).

Fourthly, travel behaviour studies are strongly driven by data and modelling issues, and they often spend much energy on adjusting models to a sample. Employing rigorous validation exercises such as working with two separate samples, as we did in this paper, can help establish more reliable associations between behavioural outcomes and the factors that predict them.

For policy it is encouraging to see that people change their behaviour rather than being ‘frozen’ in a behaviour they have developed earlier. Significant effects of PT and parking space provision suggest that modal change can be achieved even in a society with high car ownership levels. The effects found encourage 'carrot and stick' transport policies to encourage multimodal behaviours. Behavioural fluidity is also reflected in the correlations between levels of multimodality in two consecutive years. These correlations are strong, but far from deterministic. Policy strategies have already started to make use of key events in providing travel information and other incentives to people. The results presented in this paper support this idea by providing evidence for behavioural changes, e.g. when PT provision changes. The positive effect of the baseline state of the PT system on multimodality suggests that the provision of high-quality PT may continue to attract some new users over time or increase demand of occasional customers. At the same time, some socio-demographic baseline effects suggest continual change in some population groups which favours the idea that transport policies should not only focus on key events but consider continual behavioural adaption over people's life courses.

It is important to note that more multimodality does not necessarily imply more sustainable travel. More multimodality may also be the outcome when a frequent PT user starts driving to work. In order to better understand how sustainable travel can be attained by increasing multimodality it would be useful to focus on factors that increase multimodality among those who have permanent access to a car. Although we did not study interaction effects between car availability and other variables, our results suggest that limiting parking space and providing a good PT system in residential areas and for commuting encourages people to be more multimodal, and this is likely to include car owners. As a first step, this study looked at the factors that are associated with gradual changes in modal variability, but more detailed future research is warranted.

Acknowledgement: This research was partly funded by the German Research Foundation (DFG) as part of the project 'Veränderungen der Mobilität im Lebenslauf: Die Bedeutung biografischer und erreichbarkeitsbezogener Schlüsselereignisse' (Travel behaviour changes over the life course: the role of biographical and accessibility-related key events, 2015-2018). EH is supported by the Dutch Research Council fellowship (VENI-grant 016.145.073).

Literature

Buehler, R. and Hamre, A. (2015) The multimodal majority? Driving, walking, cycling, and public transportation use among American adults. *Transportation*, 42, 1081-1101.

Cao, X., Mokhtarian, P.L. and Handy, S.L. (2007) Cross-sectional and quasi-panel explorations of the connection between the built environment and auto ownership. *Environment and Planning A,* 39, 830-847.

Chatterjee, K. (2011) Modelling the dynamics of bus use in a changing travel environment using panel data. *Transportation*, 38, 487-509.

Chatterjee, K., Clark, B. and Bartle, C. (in press) Transitions in commute mode patterns and sustainable transport promotion. *European Journal of Transport and Infrastructure Research*.

Chatterjee, K. and Scheiner, J. (2015) Understanding changing travel behaviour over the life course: Contributions from biographical research. A resource paper for the Workshop "Life-Oriented Approach for Transportation Studies". Presented at the 14th International Conference on Travel Behaviour Research (IATBR), Windsor, UK, 19-23 July 2015.

Clark, B., Chatterjee, K. and Melia, S. (2015) Changes to commute mode: The role of life events, spatial context and environmental attitude. Online proceedings of 94th Transportation Research Board Annual Meeting, 11-15 January, Washington, D.C., UK.

Coulter, P.B. (1989) Measuring Inequality. A Methodological Handbook. Westview Press, Boulder.

EC (2014) Do the right mix. European Commission's Sustainable Urban Mobility Campaign. European Commission Directorate-General for Mobility and Transport. <http://www.dotherightmix.eu/campaign/do-the-right-mix> (accessed 08.09.14).

Etminani-Ghasrodashti, R. and Ardeshiri, M. (2015) Modeling travel behavior by the structural relationships between lifestyle, built environment and non-working trips. *Transportation Research Part A,* 78, 506-518.

Follmer, R., Gruschwitz, D., Jesske, B., Quandt, S., Lenz, B., Nobis, C., Köhler, K. and Mehlin, M. (2010) *Mobilität in Deutschland 2008: Ergebnisbericht*. Infas/DLR, Bonn and Berlin.

Hedeker, D., Gibbons, R.D. and Flay, B.R. (1994) Random-effects regression models for clustered data with an example from smoking prevention research. *Journal of Consulting and Clinical Psychology*, 62, 757-765.

Heinen, E. and Ogilvie, D. (2016) Variability in baseline travel behaviour as a predictor of changes in commuting by active travel, car and public transport: a natural experimental study. Journal of Transport and Health 3(1), 77-85.

Heinen, E. and Chatterjee, K. (2015) The same mode again? An exploration of mode choice variability in Great Britain using the National Travel Survey. *Transportation Research Part A,* 78, 266-282.

Heinen, E., Panter, J., Mackett, R. and Ogilvie, D. (2015) Changes in mode of travel to work: a natural experimental study of new transport infrastructure. *International Journal of Behavioral Nutrition and Physical Activity*, 12, 81.

Huff, J.O. and Hanson, S. (1986) Repetition and variability in urban travel. *Geographical Analysis*, 18, 97-114.

Jones, H., Chatterjee, K. and Gray, S. (2014) A biographical approach to studying individual change and continuity in walking and cycling over the life course. *Journal of Transport & Health*, 1, 182-189.

KIT (Karlsruher Institut für Technologie) (2012) *Das Deutsche Mobilitätspanel (MOP). Informationen zur Datennutzung*. Stand 2012 (MOP-Handbuch). KIT, Karlsruhe.

Klinger, T. and Lanzendorf, M. (2016) Moving between mobility cultures: what affects the travel behavior of new residents? *Transportation,* 43(2), 243-271.

Kroesen, M. (2014a) Modeling transitions between single- and multimodal travel patterns over time: application of latent class transition analysis. Paper presented at the Transportation Research Board 93rd Annual Meeting, 12-16 January 2014, Washington, D.C.

Kroesen, M. (2014b) Modeling the behavioral determinants of travel behavior: An application of latent transition analysis. *Transportation Research Part A,* 65, 56–67.

Kuhnimhof, T., Buehler, R.,Wirtz ,M. and Kalinowska, D. (2012) Travel trends among young adults in Germany: increasing multimodality and declining car use for men. *Journal of Transport Geography*, 24, 443–450.

Miles, A., Moore, N. and Muir, S. (2013) Mobility biographies: studying transport and travel behaviour through life histories. *Strategies for Sustainable Mobilities: Opportunities and Challenges* eds R. Gerike, F. Hülsmann and K. Roller, pp. 173-188. Ashgate, Farnham,.

Molin, E., Mokhtarian, P. and Kroesen, M. (2016) Multimodal travel groups and attitudes: A latent class cluster analysis of Dutch Travelers. *Transportation Research Part A*, 83, 14-29.

Müggenburg, H., Busch-Geertsema, A. and Lanzendorf, M. (2015) A review of achievements and challenges of the mobility biographies approach and a framework for further research. *Journal of Transport Geography*, 46, 151-163.

Nobis, C. (2007) Multimodality – facets and causes of sustainable mobility behaviour. *Transportation Research Record*, 2010, 35–44.

Oakil, A, Ettema, D., Arentze, T. and Timmermans, H. (2011) A longitudinal analysis of the dependence of commute mode switching decisions on mobility decisions and life-cycle events. Paper presented at the 16th International Conference of the Hong Kong Society for Transportation Studies.

Polk, M. (2004) The influence of gender on daily car use and on willingness to reduce car use in Sweden. *Journal of Transport Geography,* 12, 185-195.

Scheiner, J. (2011) Changes in travel mode choice: the impact of period, cohort, and life-course effects: a comprehensive approach. Raum und Mobilität – Arbeitspapiere des Fachgebiets Verkehrswesen und Verkehrsplanung 24. Technische Universität, Dortmund.

Scheiner, J. (2014) Gendered key events in the life course: effects on changes in travel mode choice over time. *Journal of Transport Geography*, 37, 47-60.

Scheiner, J. and Holz-Rau, C. (2007) Travel mode choice: affected by objective or subjective determinants? *Transportation*, 34, 487-511.

Scheiner, J. and Holz-Rau, C. (2013) A comprehensive study of life course, cohort, and period effects on changes in travel mode use. *Transportation Research Part A*, 47, 167-181.

Schwanen, T., Kwan, M.-P. and Ren, F. (2008) How fixed is fixed? Gendered rigidity of space-time constraints and geographies of everyday activities. *Geoforum,* 39, 2109-2121.

Stead, D., Williams, J. and Titheridge, H. (2000) Land use, transport and people: identifying the connections. *Achieving Sustainable Urban Form* eds K. Williams, E. Burton and M. Jenks, pp. 174-186. E & FN Spon, London.

Susilo, Y.O. and Axhausen, K.W. (2014) Repetitions in individual daily activity-travel-location patterns: a study using the Herfindahl-Hirschman Index. *Transportation*, 41, 995-1011.

Tabachnick, B.G. and Fidell, L. S. (2007) Using multivariate statistics. 5th ed., Pearson, Boston.

Thøgersen, J. (2012) The importance of timing for breaking commuters' car driving habits. *The Habits of Consumption* eds A. Warde and D. Southerton. Available from http://www.helsinki.fi/collegium/journal/volumes/volume_12/ (18/06/15)

Wagner, M. and Franzmann, G. (2000) Die Pluralisierung der Lebensformen. *Zeitschrift für Bevölkerungswissenschaft*, 25, 151-173.

Wooldridge, J.M. (2003) Cluster-sample methods in applied econometrics. *The American Economic Review,* 93, 133-138.

Yun, M., van Herick, D. and Mokhtarian, P.L. (2011) Nonwork Travel Behavior Changes During Temporary Freeway Closure: The Fix 1-5 Project in Sacramento, California. *Transportation Research Record*, 2231, 1-9.

Appendix: Regression models for validation sample

		Change in...															
		No. of modes (Model 1)				Mode entropy (Model 2)				HHI, normalised (Model 3)				Share of primary mode (Model 4)			
		B	SE	Beta	Sig.	B	SE	Beta	Sig.	B	SE	Beta	Sig.	B	SE	Beta	Sig.
Intercept		1.37	0.08		<0.005	0.29	0.03		<0.005	0.31	0.02		<0.005	0.41	0.02		<0.005
Gender female	B	0.02	0.05	0.01	0.77	0.00	0.02	0.01	0.83	0.00	0.01	0.00	0.87	0.00	0.01	0.00	0.86
Age group (ref.: 18-29 years)																	
10-17 years	B	0.24	0.08	0.06	<0.005	0.09	0.03	0.07	<0.005	-0.08	0.02	-0.09	<0.005	-0.05	0.01	-0.07	<0.005
30-44 years	B	0.00	0.05	0.00	1.00	0.01	0.02	0.01	0.66	-0.02	0.01	-0.04	0.08	0.00	0.01	-0.01	0.69
45-59 years	B	-0.03	0.05	-0.01	0.52	0.00	0.02	0.00	0.83	-0.02	0.01	-0.04	0.08	0.00	0.01	-0.01	0.74
60-74 years	B	0.03	0.05	0.01	0.54	0.04	0.02	0.05	0.03	-0.06	0.01	-0.12	<0.005	-0.03	0.01	-0.07	<0.005
75+ years	B	-0.11	0.07	-0.02	0.11	-0.01	0.02	0.00	0.79	-0.04	0.02	-0.03	0.02	-0.01	0.01	-0.01	0.62
No. of children in household (< 10 yrs)	B	0.04	0.02	0.03	0.02	0.00	0.01	0.00	0.71	0.00	0.00	-0.01	0.60	0.00	0.00	0.00	0.71
No. of children in household (10-13 yrs)	B	0.05	0.03	0.02	0.07	0.01	0.01	0.01	0.27	-0.01	0.01	-0.02	0.06	-0.01	0.01	-0.01	0.25
No. of children in household (14-17 yrs)	B	0.02	0.03	0.01	0.48	0.00	0.01	0.00	0.92	0.01	0.01	0.02	0.13	0.00	0.01	0.01	0.59
Apprenticeship, trainee, education	B	0.12	0.06	0.04	0.06	0.06	0.02	0.05	0.01	-0.03	0.01	-0.04	0.04	-0.03	0.01	-0.06	<0.005
Education level (ref.: university entrance qualification or higher)																	
Elementary school qualification...																	
...without apprenticeship or no qualification	B	-0.15	0.04	-0.05	<0.005	-0.03	0.02	-0.03	0.03	0.03	0.01	0.03	0.02	0.01	0.01	0.02	0.21
...plus apprenticeship	B	-0.12	0.03	-0.05	<0.005	-0.03	0.01	-0.03	<0.005	0.02	0.01	0.04	<0.005	0.01	0.00	0.03	0.02
Secondary school qualification level I	B	-0.11	0.03	-0.05	<0.005	-0.03	0.01	-0.04	<0.005	0.02	0.01	0.03	0.01	0.01	0.00	0.03	0.02
PT connection to workplace (reference: good)																	
No connection	B	-0.15	0.03	-0.05	<0.005	-0.06	0.01	-0.06	<0.005	0.04	0.01	0.06	<0.005	0.03	0.01	0.06	<0.005
Poor connection	B	-0.07	0.03	-0.02	0.02	-0.04	0.01	-0.04	<0.005	0.03	0.01	0.04	<0.005	0.02	0.01	0.04	<0.005
Parking situation at workplace (very) difficult	B	0.08	0.03	0.03	0.01	0.03	0.01	0.03	0.01	-0.03	0.01	-0.05	<0.005	-0.02	0.01	-0.03	0.01
PT quality in neighbourhood (variety of different systems accessible on foot)	B	0.06	0.01	0.06	<0.005	0.02	0.00	0.05	<0.005	-0.02	0.00	-0.07	<0.005	-0.01	0.00	-0.05	<0.005
Driving licence holding	B	0.05	0.06	0.02	0.41	0.00	0.02	0.00	0.86	0.01	0.01	0.02	0.49	0.00	0.01	0.00	0.94
Driving licence holding * female	B	0.14	0.06	0.07	0.02	0.05	0.02	0.07	0.01	-0.02	0.01	-0.04	0.19	-0.03	0.01	-0.07	0.01

Car availability (reference: no)																	
Occasionally / after agreement	B	0.21	0.04	0.06	<0.005	0.06	0.02	0.06	<0.005	-0.01	0.01	-0.02	0.19	-0.03	0.01	-0.05	<0.005
Regularly	B	0.02	0.03	0.01	0.57	-0.01	0.01	-0.02	0.33	0.04	0.01	0.08	<0.005	0.01	0.01	0.03	0.08
Baseline behaviour	B	-0.59	0.01	-0.56	<0.005	-0.51	0.01	-0.53	<0.005	-0.47	0.01	-0.53	<0.005	-0.54	0.01	-0.55	<0.005
Child moving out	C	0.23	0.07	0.03	<0.005	0.07	0.03	0.03	0.01	-0.03	0.02	-0.02	0.05	-0.02	0.01	-0.02	0.10
Entry into labour market	C	-0.10	0.05	-0.02	0.06	-0.05	0.02	-0.02	0.02	0.03	0.01	0.03	0.01	0.03	0.01	0.03	0.01
Leaving labour market (no retirement)	C	0.07	0.07	0.01	0.31	0.03	0.02	0.01	0.27	-0.01	0.02	0.00	0.64	-0.01	0.01	-0.01	0.30
Retirement	C	0.08	0.06	0.01	0.19	0.04	0.02	0.02	0.07	-0.03	0.01	-0.02	0.03	-0.02	0.01	-0.01	0.16
Parking situation at workplace gets much worse	C	-0.05	0.08	-0.01	0.52	0.00	0.03	0.00	0.99	-0.02	0.02	-0.01	0.34	-0.01	0.01	-0.01	0.59
Parking situation at workplace gets much better	C	0.08	0.08	0.01	0.31	0.01	0.03	0.01	0.62	0.01	0.02	0.00	0.70	0.01	0.01	0.00	0.72
Change in PT quality in neighbourhood	C	0.02	0.01	0.01	0.16	0.01	0.01	0.01	0.22	-0.01	0.00	-0.02	0.05	0.00	0.00	-0.01	0.24
Loss of driving licence	C	0.00	0.10	0.00	0.97	0.03	0.03	0.01	0.40	-0.04	0.02	-0.02	0.08	-0.02	0.02	-0.01	0.18
Achievement of driving licence	C	0.18	0.08	0.02	0.02	0.02	0.03	0.01	0.51	0.03	0.02	0.02	0.06	0.00	0.01	0.00	0.92
Loss in car availability	C	0.10	0.04	0.02	0.02	0.06	0.02	0.04	<0.005	-0.05	0.01	-0.04	<0.005	-0.03	0.01	-0.04	<0.005
Increase in car availability	C	-0.04	0.05	-0.01	0.41	-0.03	0.02	-0.02	0.05	0.03	0.01	0.03	<0.005	0.02	0.01	0.02	0.05
R^2 adj		0.293				0.256				0.234				0.271			
n		7,588				7,588				7,588				7,588			

Table 6: Regression models of changes multimodality (validation sample)

B = baseline variable; C = change variable. SE=Standard error