# Changes in travel mode use over the life course with partner interactions in couple households

Joachim Scheiner

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

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Abstract: The paper links the mobility biography approach with studies on intra-household interactions between partners in travel. It does so by developing a multi-group path model – a structural equation model without latent variables – of changes in car use over time as a function of changes in activity and trip patterns, path dependency (baseline car use), life course changes, and the respective respondent's partner's car use, activity and trip patterns. In terms of life course changes, the paper accounts for (gradual, rather than abrupt) changes in paid and unpaid worktime, and the birth of a first or higher-order (i.e. second or further) child. The model further categorises respondents by gender. It focuses on couples who share one car. A model for multi-car households is estimated for comparison. The results show multiple interactions between two partners at the baseline as well as over time. The effects of the birth of a child are less clear than expected. Generally, they suggest that increases in driving are primarily an outcome of higher-order births, especially in one-car households. Policy conclusions are (1) that it may be overly optimistic to assume that the birth of a child can be utilised as a 'window of opportunity' to reduce driving, and (2) that social interactions between partners should be taken into account in policy concepts.

Keywords: mobility biography; life course; travel behaviour change; car use; intra-household interactions; gender; child birth

## 1 Introduction

The past fifteen years have seen a tremendous increase in research in travel behaviour change. This includes studies about short-term, day-to-day variability and longer-term change. The interest has been motivated, on the one hand, by the evaluation of travel demand management programmes for change, such as personalised travel planning (Meloni et al., 2017; Davies, 2012; Bamberg et al., 2011; Skarin et al., 2017), or the effects of infrastructure provision (Spears et al., 2017; Cao and Ermagun, 2017; Termida et al., 2016) aiming to achieve more sustainability in transport. On the other hand, researchers seek to understand how and why travel behaviour changes over time throughout people's life courses (Oakil et al., 2014; Chatterjee and Scheiner, 2015; Rau and Manton, 2016; Beige and Axhausen, 2017; Scheiner, 2018).

A large portion of these latter approaches, often labelled mobility biographies, focus on the effects of transitions from one stage in the life course to another (e.g. from unemployment to employment) and associated life events (here: finding a job). Fewer studies look at more gradual changes that may be induced by learning processes and coping strategies used to adapt to changing circumstances, although some studies seek to better understand lagged or lead (anticipated) reactions to events (Oakil et al., 2014; Guo et al., 2019). Plyushteva and Schwanen (2018) highlight the diversity of shorter and longer-term, gradual and abrupt temporalities that interfere with each other (for a quantitative approach to this see Zhang et al., 2014). Life courses are embedded in multiple social relationships, as expressed by sociological and psychological terms such as 'linked lives' and 'socialisation', but after all, a life course is, by definition, an individual affair. This may be the reason why few studies have taken into account the effects of the events and changes a person experiences on their partner's or family's travel (but see Plyushteva and Schwanen, 2018; Rau and Sattlegger, 2017).

The links between travel and social networks within and beyond the household are another field in transport studies that has risen in parallel over the past fifteen years. This field is arguably at least as wide as the life course approach, and involves multiple facets of both social networks and travel dimensions. Yet linking the two fields is an undertaking that remains to be tackled. Perhaps closest to this is the work done by Sharmeen (2014a, 2014b, 2015); see also the conceptual work done by Axhausen (2002); for a practice-theoretical approach see Rau and Sattlegger (2017). Recent comprehensive surveys will likely result in more related research (Scheiner et al., 2014; Calastri et al., in press).

This paper contributes to research by studying changes in travel mode use from one year to the next as a function of events and more gradual changes experienced by individuals and their partners. Gradual changes also include the two partners' individual activity and travel patterns. The paper utilises the German Mobility Panel (GMP), national panel data collected every year. The paper is novel in two respects. Firstly, it links life-course changes in travel with interactions between partners. Secondly, it looks at gradual changes while the bulk of the mobility biographies literature studies categorical transitions from one life stage to another.

The next section briefly introduces the literature. Section 3 introduces the data and methodology. Section 4 provides the results, and Section 5 gives a summary and conclusions.

## 2 State of the research

Two lines of research are most relevant for this paper. Firstly, the literature on mobility biographies (Section 2.1) and, secondly, the literature on intra-household interactions in travel (Section 2.2). This journal has played a prominent role in both fields (see Beige and Axhausen, 2017; Clark et al., 2016b; Delbosc and Nakanishi, 2017; Scheiner and Holz-Rau, 2013, for the former, and Kroesen, 2015, for the latter field). Both have grown into huge fields and, hence, the paper cannot take full account of either of them. See for recent overviews

- on mobility biographies: Jones et al. (2014), Müggenburg et al. (2015), Chatterjee and Scheiner (2015), Rau and Manton (2016), Delbosc and Nakanishi (2017); Beige and Axhausen (2017), Greene and Rau (2018), Scheiner (2018);
- on travel behaviour change in a wider sense: Rasouli and Timmermans (2017), Friman et al. (2017), Skarin et al. (2017);
- on intra-household interactions (i.e. interactions between household members) in travel: Ho and Mulley (2015), Auld and Zhang (2013), Yu, Zhang and Fujiwara (2013), Kato and Matsumoto (2009), Kang and Scott (2011), Schwanen et al. (2007), Ettema and Van der Lippe (2009), Kroesen (2015);

- on the links between wider social networks beyond the household and travel: Kim, Rasouli and Timmermans (2017), Pike and Lubell (2016), Sadri et al. (2015), Arentze (2015), Goetzke et al. (2015), Lin and Wang (2014), Dugundji et al. (2011) and other papers in the same issue; Larsen et al. (2006). For family networks beyond the household see Rubin and Bertolini (2016), and Rau and Sattlegger (2017); for leisure contact Kowald et al. (2015); for wider social influence Sherwin et al. (2014), Abou-Zeid et al. (2013).

### *2.1 Mobility biographies*

After the turn of the millennium, the idea of a life-course-oriented (or biographical) approach to travel began to take explicit shape (Axhausen, 2002; Lanzendorf, 2003; Van der Waerden et al., 2003). This profited from a number of research strands, including life course approaches in various disciplines, time geography, and early studies on travel behaviour change using the emerging panel surveys to look at longer-term variability in mobility (Goodwin, 1989). The theoretical ideas of this approach are based on a number of key elements (Scheiner, 2018).

One basic idea is that travel behaviour tends to be stable over time due to habits, which results in strong path dependency in behaviour. Significant changes may, however, be motivated by transitions, events and learning processes, and gradual adaptations to changing circumstances over an individual's biography, and the break of routines. This links mobility biographies to other domains of the life course in which such events and processes may occur, including the residential biography, educational and employment biography, household biography and the wider family and social network, and other life domains such as health. Actually, the majority of empirical work in the field to date focuses on the impact of key events (or life events, life-cycle events, life course events) and transitions on travel, i.e. mostly on mode choice. This includes events (1) in the family and household biography, such as leaving the parental home; forming a household; birth of a child; separation from one's partner; a child moving out of the parental home (Clark et al. 2016a, 2016b on changes in household composition/size, McCarthy et al., in press, on child birth, Oakil, 2013, and Scheiner and Holz-Rau, 2013, on various household/family events), (2) in the educational and employment biography, such as starting an apprenticeship or higher education; entering the labour market; change of workplace (Oakil 2013, Clark et al. 2016b); income change (Clark et al. 2016a); transition between employment and unemployment (Clark et al. 2016a, Rasouli et al. 2015); retirement (Oakil, 2013); (3) in the residential biography, i.e. residential relocation and associated changes in accessibility (Handy et al., 2005; Prillwitz et al., 2006; Oakil, 2013; Clark et al., 2016b).

Over and above individual events, it has been recognised that life courses are socially embedded. The impact of socialisation agents such as family members, schools or peers, suggests interpersonal links in biographical processes in mobility. In an even wider societal context, mobility biographies can be understood as being embedded in historical circumstances and processes in time and space. Hence, different levels of stability and change (individual/collective/regime) need to be distinguished (Scheiner, 2018).

Practically spoken, such 'macro' processes in time and space have been studied in terms of events caused by transport system disruptions (Danczyk et al., 2016; Marsden and Doherty, 2013, Pnevmatikou et al., 2015), transport demand management concepts (Uttley and Lovelace, 2016) or mega events (Parkes et al., 2016) that may promote (short-term or long-term) behavioural changes, though not directly related to the life course. Little has been done to understand the linkages between macro-societal processes and individual life courses in travel, such as the institutionalisation of long-distance travel (but see Frändberg, 2006).

Reliance on the statistical significance of cause-impact relationships has raised criticism of the mobility biographies approach (Rau and Manton, 2016), and indeed most mobility biography studies focus on life course research rather than biography research. Life course is typically conceived as a sequence of events and role transitions that a person lives through from birth to death (Elder et al. 2006). In contrast, a biography is understood as a subject's self-reflective, meaningful action within the temporal structure of his or her own life (Sackmann 2007). Accordingly, biography studies reconstruct subjective meaning while life course studies attempt to objectively measure sequences and structures in people's lives, e.g. by inquiring about predefined stations, events or sequences. Nevertheless this paper utilises the term mobility biography, which has been used widely for related research in the past decade.

### *2.2 Travel and intra-household interactions*

Interdependencies (or interactions) in travel between household members have long been recognised, as reflected in the use of household type as a variable to explain travel. Such interdependencies have multiple reasons and can take multiple forms. They may refer to activity and trip patterns of household members, as well as to mode choice.

In terms of mode choice, many couples share a car and, thus, the car is only available to one partner at a time (unless the two make joint trips). The use of the car thus needs to be negotiated (Scheiner and Holz-Rau, 2012; Delbosc and Currie, 2012; Blumenberg et al., 2019). On the other hand, there may be positive correlations between the mode choices of several household members due to joint trips, socialisation effects or the shared economic situation. There is recent evidence for such socialisation effects in terms of the impact of parents on their children (Taubman-Ben-Ari et al., 2005; Haustein et al., 2009; Park et al., 2013; Kamargianni et al., 2014; Susilo and Liu, 2016) and – less so – spouses on each other (Kroesen, 2015). This research generally finds positive behavioural links, suggesting that conformity in behaviour predominates over nonconformity (Sunitiyoso et al., 2013).

In terms of activity patterns, a basic form of interaction is the undertaking of joint trips and activities, especially for leisure purposes (Simma and Axhausen, 2001; Gliebe and Koppelman, 2005; Nurul Habib et al., 2008; Kato and Matsumoto, 2007; Lim, 2012; Rau and Sattlegger, 2017), but also in terms of chauffeuring or escorting household members without necessarily sharing the activity at the destination. This has been studied extensively with respect to escorting children to school (e.g., Scheiner, 2016b) and children's mode choice to school (e.g., Chen et al., 2018).

On the other hand, household economics suggest intra-household worksharing with respect to paid and unpaid work, which has been frequently studied from a gender perspective (Simma and Axhausen, 2001; Schwanen et al., 2007; Ettema and Van der Lippe, 2009). This suggests solo rather than joint trips for reasons of efficiency. Again, this can be seen in child escort which is very rarely undertaken on a joint basis by two parents (Scheiner, 2016b).

The fundamental difference between the two is shown clearly by Dharmowijoyo et al. (2017) who use a three-week time-use and activity diary collected in Indonesia. They show that the complexity of an individual's activity-travel pattern correlates negatively with the complexity of other household members' activity-travel patterns when individuals need to share household obligations with other household members (as is typically the case on weekdays), while the same correlation is positive at weekends when individuals tend to perform joint activities with other household members. Such interactions may often be traced back to temporal regimes, including business times, shopping hours, or school start and end times (Deka, 2017) that act as spatio-temporal 'pegs' in daily life (Schwanen et al., 2008). This has led to research on the coordination (synchronisation and de-synchronisation) of work schedules in families (Gupta and Vovsha, 2013, Carriero et al., 2009).

Last, but not least, the choice of residence is often considered a long-term decision that affects short-term travel choices. Residential self-selection can thus be regarded as a case of interaction between household members, and the negotiations about this choice between partners is only beginning to be studied in transport research (Guan and Wang, 2019).

### *2.3 Linking intra-household interactions with mobility biographies*

Little work has been done to explicitly link life course approaches to travel with intra-household interactions (or wider social networks), although many studies include household-related variables that may be seen as proxy variables to capture interactions (e.g., change in household car ownership). Axhausen (2002) provided conceptual thoughts on the links between individuals' social networks and the dynamics of their travel patterns (especially their activity spaces). While focusing on day-to-day variability, he also took into account people's longer-term projects and commitments, which links his work to mobility biographies that have been worked out in more detail by Ohnmacht (2009). Other early conceptual work on mobility biographies (Lanzendorf, 2003; Scheiner, 2007) also included the household and family context, but with little emphasis on working out the details of intra-household interactions.

Sharmeen et al. (2014a) study changing activity and trip durations in reaction to life events and the evolution of social networks over the life course, taking path dependence into account. In a companion paper, Sharmeen et al. (2014b) study face-to-face contact frequency with close alters as a function of life events, accessibility changes and other variables, and in another paper, (2015) the same authors use life events as triggers to investigate the evolution of social networks. Social networks here are irrespective of household or family membership.

Lee and Goulias (2019) use the US-based Puget Sound panel to look at whether travel mode attitudes are homogeneous between partners living in a household, and find they are not. They 'follow' a sample of households over ten years to explore the sequences in their residences, car ownership and travel, finding distinct patterns according to the (combination of) attitudes within households.

In a very different methodological approach guided by practice theory, Rau and Sattlegger (2017) use nine qualitative interviews with couples in Vienna to study the multitude of mobility practices related to couple and family relationships including the partners' wider family networks. They retrospectively unfold the practices and meanings of shared mobility over the life course, starting with young couples living in separate households and ending with grandparenthood.

Plyushteva and Schwanen (2018) also use qualitative interviews in London and Manila to study intra-family interactions in care over time including family relations beyond the household. They highlight that such changes over time do not necessarily relate to discretionary events, but there are various temporalities that intersect and interfere with each other (see Zhang et al., 2014, for a quantitative approach to overlapping time scales). They also demonstrate the large variety of such changes over time that can hardly be studied using quantitative methods such as regression analysis, as these are based on mean estimations.

As can be seen, the few available studies that link mobility biographies with interpersonal inter-dependencies strongly demonstrate that social interaction (within and beyond the household) contributes to understanding mobility biographies. Little work to date uses standardised data to focus exclusively on intra-household interactions in mobility biographies. This paper does exactly this. It is based on the general hypothesis that life events and gradual changes in social roles over time (such as paid and unpaid worksharing) may affect an individual's and his/her partner's trip pattern and mode choice.

# 3 Data and method

## *3.1 Data*

The analysis presented in this paper makes use of the German Mobility Panel (GMP) 1994 to 2016[1]. The GMP is a 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. A trip diary is used to collect information on trips and associated activities at the destination over a whole week from all household members aged ten years or over. The seven-day record allows activity and trip patterns on the individual level to be detected, while this is not possible with single- or two-day activity/trip diaries. This is because a week represents the typical temporal organisation of daily life. Sociodemographic attributes for the household and its members are collected, as are spatial context attributes at the residence and at the household members' places of work or education.

Household income has only been recorded since 2002, with an interruption in 2003, which considerably reduces sample size for any analysis including income. Coding life course events results in missing values in many cases (see Scheiner, 2011, for details). As life course events are relatively rare events in an individual's life, in cases of uncertainty no event is assumed. The coefficients estimated are thus based on changes among those for whom an event occurred, while some of those for whom no event is assumed may in fact have experienced one. Another limitation is that, as in most other German data, there are no small-scale geocodes available.

The analysis is limited to couple households with two licences who share a car. This is based on the assumption that life course changes have less effect on car use among couples in which each partner has his/her own car. Cases of households who purchase additional cars or give up their car from one year of observation to the next are excluded as this would require additionally controlling for changes in car ownership which would add further complexity to the models.

Models for multiple-car couples were estimated additionally. Key results from these models are included in the results section as appropriate, especially for the effects of the birth of a child on driving. The full models are available on request. From previous research it may be expected that some effects of life course changes on car use differ between men and women (Scheiner, 2014). Hence multi-group models are employed to test for gendered effects.

For some respondents there are two observations of change available, i.e. from the first to the second and from the second to the third year of report, which violates the basic assumption of independent observations. A subsample including only one random observation per couple is used to ensure independence, although the results strongly resemble a model that includes the whole sample. The final net sample includes 1,947 women and 1,867 men (total n=3,814), for which complete information (other than that discussed above) is available.

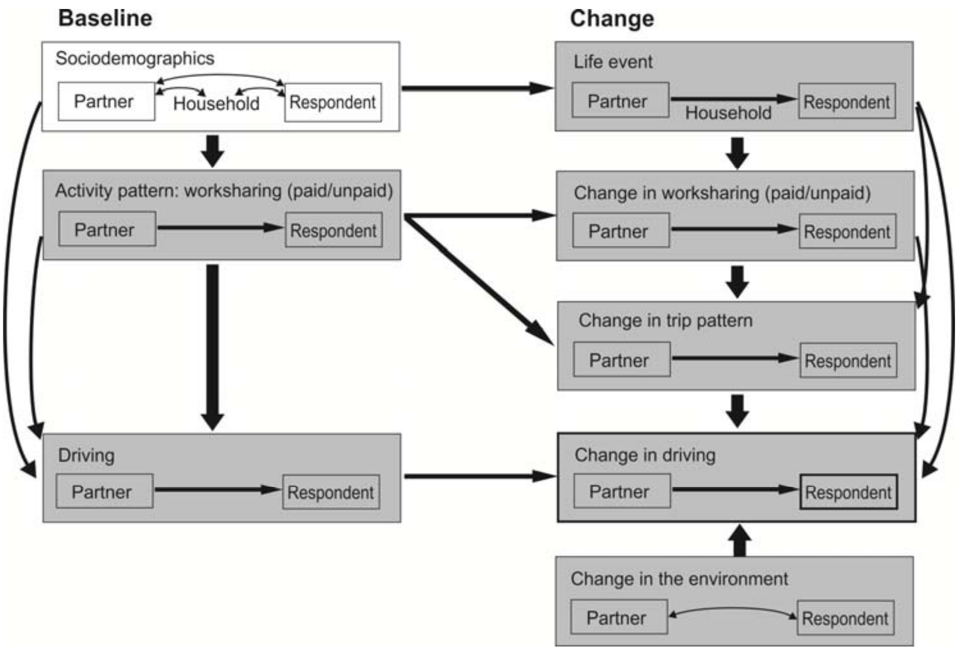
## *3.2 Modelling approach*

The model structure used largely follows basic assumptions in travel behaviour research (Figure 1). Changes from one year to the next are modelled dependent on baseline values in the previous year to account for path dependency. Changes in activity and trip patterns are considered a function of life events. Additionally, changes in trip patterns are modelled as a function

[1] The GMP is conducted by the University of Karlsruhe on behalf of the Federal Ministry of Transport, Building and Urban Development (BMVBS). The data are provided for research use by the Clearingstelle Verkehr (www.clearingstelle-verkehr.de).

of activity patterns (and associated changes), in line with the activity-based approach to travel. Finally, changes in mode use are considered dependent on changes in trip and activity patterns, and life events. At the same time, the respondent's variables are modelled as a function of his/her partner's variables, while household-related variables such as child birth are seen to refer to both partners. While some studies have included two-way relationships or looked at group decision making in households (see special issue in Transportation Research Part B 43(2), Timmermans and Zhang, 2009; Gliebe and Koppelman, 2005), this paper defines the behaviour of a particular respondent as the outcome of interest. His/her partner's behaviour is consequently assumed to impact this behaviour. This is modelled simultaneously, but separately, for men and women. If two-way relationships were allowed, a multiple-group model would not make sense, as men's effects on women and women's effects on men would appear in both groups likewise.

**Figure 1: Model structure**




The white box is excluded from the final model. Arrows are paths, double-headed arrows are correlations.

Changes in the environment are modelled as exogeneous influences. Baseline trip patterns are excluded to keep the model parsimonious. In initial model versions life events were considered dependent on baseline sociodemographics, but the latter were finally excluded (see below).

There are a potentially almost infinite number of variables that can be argued to reflect 'activity pattern' or 'trip pattern'. The variables specifically used are described below.

### *3.3 Path analysis*

The paper is based on path analysis, which is a special case of structural equation modelling (SEM). SEM is a powerful statistical tool that can be seen as a combination of factor analysis and extended regression modelling. In the factor analysis part, latent variables are represented by a number of observed variables each, and enter the model via measurement models. The causal relationships between various exogeneous and endogeneous variables are captured by a structural model. Path analysis is limited to a structural model capturing relationships between observed variables (i.e. the 'extended regression modelling part') and makes no use of latent variables.

Other than standard statistical procedures such as regression analysis, SEM can model mediating variables that are affected by other variables while at the same time affecting yet other variables. In this way, SEM (and path analysis) can be used to model the direct, indirect and total effects of a variable on another. Indirect effects are those that are mediated by other variables. Total effects are the sum of direct and indirect effects.

Both SEM in general and path analysis in particular have become common in transportation research in the past decades. A majority of studies appears to use path analysis (Maat and Timmermans, 2009; van Acker and Witlox, 2010 and 2011; Ding and Lu, 2016; Abreu e Silva and Melo, 2018), although latent variables are frequently used for subjective measures such as attitudes or sense of place (Deutsch et al., 2013), mode use frequencies (Kroesen, 2015) or activity durations (Sharmeen et al., 2014a). In this paper latent variables are not required, as various measures of travel, activity patterns and events can be (and have been) directly measured (other than, e.g., more opaque, theoretical constructs such as lifestyle).

The paper employs a multi-group analysis with men and women being the groups. This means that the analysis starts with a model in which all parameters are constrained to be equal across groups. In a further step parameters are allowed to vary between the groups (unconstrained model). The fit of the two models is compared to evaluate which model performs better (Baltes-Götz, 2006).

The standard estimator for SEM is Maximum Likelihood (ML), but this estimator requires multi-variate normality. On the other hand, ML is "widely used in practice regardless of the distribution of the data" (Deng et al., 2018, 8) as it has been found to produce robust results even when the normality assumption is violated, as long as the sample size is large relative to the number of parameters to be estimated (Bentler and Chou, 1987; Golob, 2003; Schermelleh-Engel et al., 2003). For instance, Etminani-Ghasrodashti and Ardeshiri (2015) compare three different estimators implemented in the software AMOS (Asympotically Distribution-Free, Generalised Least Squares, and Unweighted Least Squares) to estimate a model that includes categorical dependent variables. They find that all of them lead to very similar results.

The software package Mplus includes a large number of estimators suitable for categorical and other non-normal data, and many of them have been used in transport studies with ordered, binary or count dependent variables. They include the WLSMV (Van Acker and Witlox, 2010 and 2011; Deutsch et al., 2013; Schwanen and Wang, 2014), WLS (Xing and Handy, 2011; Abreu e Silva and Melo, 2018), MLMV (Van Acker et al., 2014), and Maximum Likelihood with robust standard errors (MLR) (Parady et al., 2018). Still others use ML with bootstrapping to reduce the bias in standard errors resulting from the violation of non-normality (Lin et al., 2018). Van den Berg et al. (2017) use ML in a life-course analysis including discrete life events, but at the price of omitting sociodemographic effects on life events. This paper employs ML. The reasoning for this decision is outlined in the following section.

### 3.4 Model development

In the analysis presented here the only categorical variables used are life events. Child birth, subcategorised by either a first or higher-order (i.e., second or further) child, was tested as an event on the household level, and the following life event variables on the individual level for the respondents and their partners, respectively: commencement of job training, apprenticeship, or university entry; entry into the labour market; change of job or education; leaving the labour market into unemployment; change in access to place of work or education; retirement. Concerning changes in worktime, it was found that models measuring time spent on paid or unpaid work by continuous variables of time-use outperform models using categorical variables of employment in terms of explained variance.

Various variables of baseline and change in the built environment were tested that turned out to be insignificant and were subsequently removed from the models. This includes urbanity at the residence, the quality of the public transport connection to work, and residential moves to either a more central or more peripheral location (see Scheiner, 2011, for details of the definitions). The same is true for a variable measuring baseline values and changes in activity pattern entropy (i.e. the mix of activities performed in the week of report).

Finally, the only remaining categorical variables were the birth of either a first or higher-order child. This distinction by birth order was deliberate, as one may assume that the effects on mode choice vary, and because this is relatively novel in transport studies (Herget, 2013; Scheiner, 2016a). This distinction results, however, in very small numbers of observations. Thus, baseline sociodemographics (income, age and education level of both partners) were tentatively excluded, which dramatically increases sample size, mainly because the resulting sample includes observations prior to 2002 when income was not yet recorded. As the model versions with and without baseline sociodemographics were very similar to each other, a decision was made to follow Van den Berg et al. (2017) and present the model without baseline sociodemographics based on a larger sample.

For the model development process the WLSMV estimator implemented in Mplus was used. ML estimations using AMOS were run for comparison. Separate models for men and women were built first. In a stepwise process non-significant variables were deleted. Variables that were significant (or close to significance, $p<0.10$) in either the model for males or females were retained in both models. The stepwise exclusion process was as follows. Life event variables that correlate only weakly with each other were first included jointly in the model, but excluded one after another while the modified model was run after each step to check for changes. The built environment variables tested are more strongly correlated. In this case a variable may easily turn out significant as soon as another, correlated, variable is excluded. Hence, all built environment variables were tested jointly, but also separately. Once a built environment variable was excluded from the model, it was allowed to re-enter once another built environment variable was excluded. The main result of this exercise was that the built environment generally showed little effect on change in driving.

In a second stepwise process the models were adjusted to the data using modification indices. Error covariances and some (non-significant) paths were entered until a good model fit was achieved. The author did not aim to perfectly adjust the models, because this implies releasing all constraints, which leads to trivial results.

Finally baseline sociodemographics were excluded, as outlined above. This implied that categorical variables were now only used as exogeneous variables, which allows for the use of the ML estimator. ML was used with bootstrapping (500 samples) which yields reliable standard errors (Deng et al., 2018, 9) to estimate the final model versions. The final model includes 204 parameters to be estimated, and 3,814 observations, which gives confidence in the suitability of the sample, as the ratio between sample size and number of parameters is typically recommended to be at least 5 to 1 for ML (Hoogland und Boomsma, 1998; Deng et al., 2018).

### *3.5 Variables used*

The final outcome variable is change in car use from one year to the next. Car use is measured as the percentage of trips made as a driver (see Lin et al., 2018, for a discussion of change score variables). The same model was also estimated using change in the absolute number of trips made as a driver. The results from these models are similar to those presented here, but different in that there is strong natural correlation between the number of trips driven and the number of trips overall. Hence the model using the percentages of trips driven is presented here which reflects more of a relative inclination to drive, given a certain trip pattern.

According to the procedure outlined above the following variables were retained in the final models (see Table 1 for descriptives).

- Child birth (yes/no). A distinction is made between first and higher order births;
- Baseline value and change in paid work and unpaid work for both partners. Both are measured on a continuous basis (hours per day) rather than as discretionary events to account for gradual changes;
- Baseline value and change in both partners' trip patterns. This is measured by (1) mean number of trips per day and (2) mean number of trips per trip chain in the week of report to account for the complexity of trip patterns.
- Baseline car use (share of trips made as a driver).

**Table 1: Descriptives of the variables used**

| | | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Mean | Min | Max | SD | Mean | Min | Max | SD |
| | **One-car households** | | | | | | | | |
| Baseline | Paid work (mean hours/day) | 2.73 | 0 | 11.55 | 2.97 | 1.61 | 0 | 9.36 | 2.21 |
| | Unpaid work (mean hours/day) | 0.55 | -0.04 | 10.76 | 0.62 | 0.66 | 0 | 8.60 | 0.56 |
| | Percentage of trips made as a driver | 0.53 | 0 | 1 | 0.30 | 0.29 | 0 | 1 | 0.29 |
| Change in… | Paid work (mean hours/day) | 0.00 | -0.14 | 0.19 | 0.03 | 0.00 | -0.11 | 0.12 | 0.02 |
| | Unpaid work (mean hours/day) | 0.00 | -0.15 | 0.07 | 0.01 | 0.00 | -0.11 | 0.08 | 0.01 |
| | Number of trips (per day, mean) | -0.09 | -5.39 | 4.22 | 1.15 | -0.04 | -6.29 | 4.34 | 1.18 |
| | Number of trips per trip chain (mean) | 0.04 | -13.27 | 40.40 | 1.38 | 0.03 | -17.00 | 34.90 | 1.49 |
| | Percentage of trips made as a driver | 0.00 | -1.00 | 0.92 | 0.23 | 0.01 | -0.70 | 1.00 | 0.22 |
| | Walking distance from public transport stop to work (in 10 min units) | 0.01 | -2 | 2 | 0.37 | 0.01 | -2 | 2 | 0.33 |
| House-hold | Child birth (first child) | 0.9% | | | 0.10 | 0.9% | | | 0.09 |
| | Child birth (higher-order child) | 1.8% | | | 0.13 | 1.7% | | | 0.13 |
| | n | 1,947 | | | | 1,867 | | | |
| | **Multi-car households** | | | | | | | | |
| Baseline | Paid work (mean hours/day) | 3.99 | 0 | 12.45 | 2.88 | 2.40 | 0 | 11.67 | 2.38 |
| | Unpaid work (mean hours/day) | 0.47 | 0 | 9.94 | 0.56 | 0.67 | 0 | 14.97 | 0.69 |
| | Percentage of trips made as a driver | 0.71 | 0 | 1 | 0.27 | 0.58 | 0 | 1 | 0.30 |
| Change in… | Paid work (mean hours/day) | 0.00 | -0.17 | 0.17 | 0.04 | 0.00 | -0.18 | 0.16 | 0.03 |
| | Unpaid work (mean hours/day) | 0.00 | -0.16 | 0.11 | 0.01 | 0.00 | -0.22 | 0.11 | 0.01 |
| | Number of trips (per day, mean) | -0.12 | -4.96 | 6.22 | 1.24 | -0.08 | -7.29 | 6.49 | 1.36 |
| | Number of trips per trip chain (mean) | -0.01 | -22.38 | 22.13 | 1.32 | 0.00 | -7.43 | 11.81 | 0.92 |
| | Percentage of trips made as a driver | 0.00 | -1 | 1 | 0.22 | 0.01 | -1 | 1 | 0.23 |
| | Walking distance from public transport stop to work (in 10 min units) | -0.01 | -2 | 2 | 0.44 | -0.01 | -2 | 2 | 0.41 |
| House-hold | Child birth (first child) | 0.5% | | | 0.07 | 0.5% | | | 0.07 |
| | Child birth (higher-order child) | 1.8% | | | 0.13 | 1.9% | | | 0.14 |
| | n | 1,875 | | | | 1,738 | | | |

Values for women are partner values in the male model part, and vice versa.

# 4 Results

## 4.1 Model fit

There are various indices to assess the model fit of an SEM. They are grouped into three types. Absolute fit measures can be used to assess the extent to which a model fits the data. The most important among these is the Chi-Square value which should not be significant, as significance implies that the empirical covariance matrix does not match the model. As large samples often result in rejection of the null hypothesis (i.e. significance), other absolute fit indices should be reported as well (e.g. RMSEA). The second group, incremental fit indices, compares the Chi-Square value with the value for a baseline model (e.g., CFI, NFI, TLI). The third group comprises parsimony fit indices that penalise for model complexity (e.g., CMIN/DF, AIC). In the case of this paper, all indices reflect a good fit (Chi-Sq=612.059, CMIN/DF=2.391, TLI=0.912, CFI=0.941, RMSEA=0.029) (Hooper et al., 2008). The Chi-Square value of the constrained model that assumes no differences across the gender groups is Chi-Sq=643.129. The improvement in model fit by allowing for differences across groups can simply be calculated as the difference in Chi-Square values (Baltes-Götz, 2006), which is 643.129-612.059=31.07. This means that the multi-group analysis performs better than a single-group analysis, but not significantly better (difference in df=128). However, the multiple pairwise significant differences in parameters (see below) should justify the use of the multi-group model.

The proportions of explained variance of change in driving vary between 16.4 (women) and 17.3 percent (men) for the models presented here (Figure 2), and between 28.7 (women) and 42.4 percent (men) for models based on daily driving trip rates. The better values for the latter are due to strong correlations between driving trip rates and overall trip rates. This is in line with values achieved in regression models based on the same data with considerably more variables, but less complexity in model structure (19.3 percent for women, and 22.4 percent for men, Scheiner, 2014).

## 4.2 Structural models

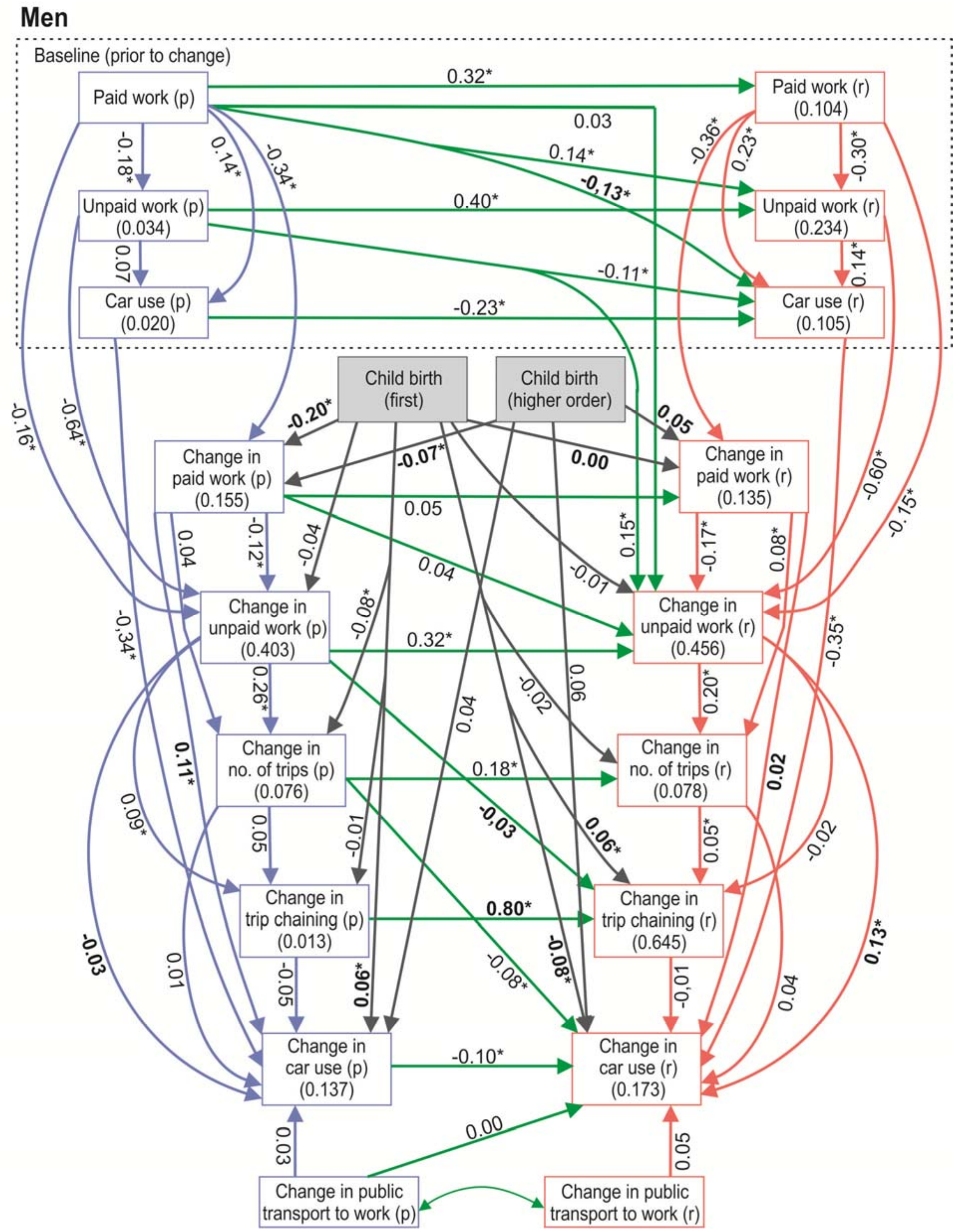
The presentation of results begins with some observations of cross-sectional activity patterns in the baseline year, and ends with the role played by the birth of a child. In order to gain a more nuanced picture of the magnitude of child birth effects on car use including indirect effects, the total effects for these events are discussed in some more detail. Otherwise, total effects are only referred to in cases where they notably add to interpretation, e.g. when they strongly differ in magnitude from the direct effects. The full matrix of total effects is in the Appendix.

### 4.2.1. Baseline activity patterns and car use

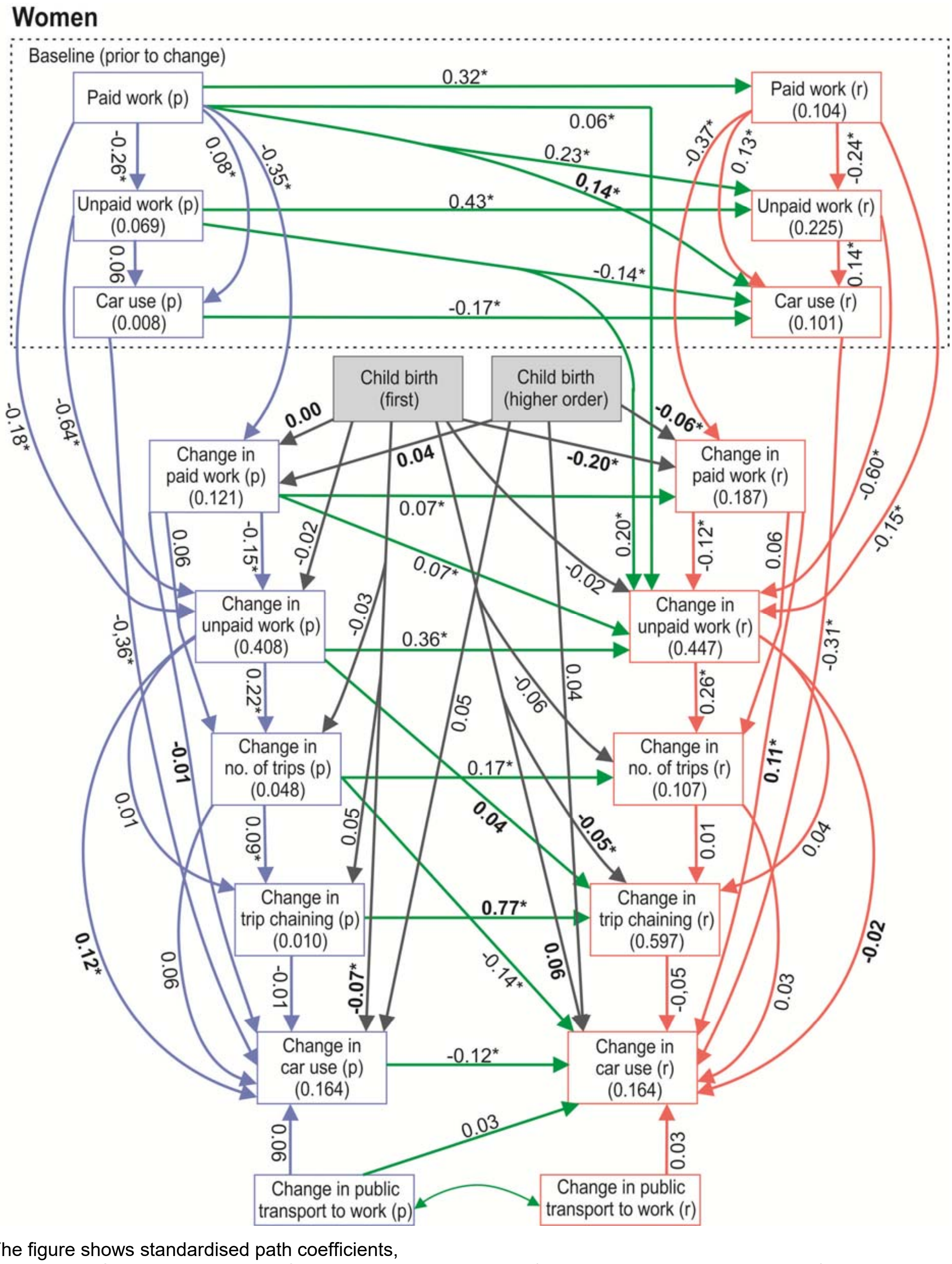
Paid and unpaid work are negatively correlated, suggesting the well-known intra-household specialisation and temporal constraints (Figure 2). Between partners, both paid and unpaid work interact positively, i.e. the more one of two partners works, the more the other one works as well. This does not seem to be due to an age effect (retired versus younger couples) as the same was found in a model controlling for both partners' age. Rather, there seems to be synchronisation at work which may be due to the specificities of the week of observation. Driving is positively associated with paid work and, less strongly, unpaid work, confirming earlier analysis of car access in one-car couples (Scheiner and Holz-Rau, 2012).

Driving is negatively correlated between partners, which appears logical as the couples share a car – the more one partner drives, the less the other. In the case of multi-car households (no figure), this is the only association with a reversed sign, i.e. in multi-car households the car use of two partners is positively correlated, suggesting that some of these couples generally tend to solo-drive more, while others drive less, confirming findings for commuting (Plaut, 2006).

**Figure 2: Final path model of change in driving**



(Figure 2, continued)




The figure shows standardised path coefficients,
proportions of explained variance of the endogeneous variables (numbers in brackets in the boxes),
the significance of coefficients (p=0.05) (asterisks)
and significance of the difference between men and women (path coefficients bold).
r: respondent. p: partner.
Red paths refer to the respondent, blue arrows to the partner, green paths are partner-respondent interactions, and black paths refer to effects of child birth.

What is more, a partner's paid workload positively affects a respondent's unpaid workload, suggesting some worksharing, but note that the total effect is considerably weaker than the direct effect. The effect of a partner's paid work on a respondent's driving depends on gender. Men drive less if their wives contribute more time to income generation, while women drive more if their husbands contribute more time to income generation. This suggests that men tend to leave the car to their working wives, while women do not. Both associations are confirmed by the total effects.

### 4.2.2. Changes in activity patterns

Both change in paid and unpaid work depend strongly, and negatively, on baseline amounts, suggesting strong path dependence in terms of the well-known phenomenon of ‘regression to the mean’ – behavioural extremes are likely to converge towards the mean over time.

Effects of baseline paid work on change in unpaid work are negative as well, although less pronounced, suggesting that there is some cross-activity adjustment over time. For instance, people with long paid work hours not only tend to reduce these, but also tend to reduce their household workload. Note, however, that this only refers to direct effects, while the total effects are weakly positive, which is due to the mediation by baseline unpaid work and change in paid work.

As for baseline time use, there is some negative effect of change in paid work on change in unpaid work, suggesting temporal constraints. There is only weak (though, in the female model, significant) positive interaction between two partners in terms of change in paid work, but when it comes to unpaid work, the interaction is quite strong, suggesting that couples synchronise their change. For instance, they may simultaneously increase their shopping. As in the baseline case, this may again suggest joint activities rather than attempting to efficiently share out-of-home unpaid work.

On the other hand, a partner's baseline unpaid workload positively affects a respondent's change in unpaid work, i.e. individuals tend to increase their unpaid work if their partner is overburdened. It is important to note that this effect changes its sign when it comes to the total effect. As can be seen from the total effect, a partner's baseline unpaid workload negatively affects a respondent's change in unpaid work, which is primarily mediated via the respondent's baseline unpaid work.

The partner's paid work amount also positively affects a respondent's change in unpaid work, but the association is weak and only significant for women who perhaps tend to relieve their working husbands somewhat more than vice versa.

### 4.2.3. Changes in trip patterns

As with activity patterns, two partners' changes in trip patterns over time are positively associated. This is very distinct for trip chaining, and less so for the number of trips.

Increases in workload result in more trips being made, and this is more pronounced for unpaid than for paid work, presumably because more paid worktime does not necessarily imply more commute trips, while more shopping or childserving (unpaid work) normally results in more trips being made. More unpaid work also leads to more trip chaining, but only for female partners in the husbands' model. More trips being made result in more trip chaining, but this is only significant for men. The associations between paid work and trip chaining were excluded from the model due to lack of effect.

### 4.2.4. Effects of activity and trip patterns and public transport to work on car use

As with baseline car use, changes in car use are negatively correlated between partners, although the association is weaker for changes than for baseline behaviour. There is no relationship between two partners' changes in driving over time in multi-car households.

Increases in paid work enhance car use, but only for women, while increases in unpaid work enhance car use for men, but not for women. It seems as if individuals are motivated to drive more, or have an argument in negotiations about car access, only if they increase those activities that are less 'normal' in their respective gender role. Changes in trip patterns have little direct effect on individual car use, but an increase in the number of trips made by a respondent's partner decreases the respondent's car use. Again this suggests some negotiation around car use in partnerships.

Changes in public transport to work do not exhibit any significant effects on car use in the final models.

### 4.2.5. The role of child birth

The effects of the birth of a child differ between men and women. For men, the birth of a first child increases trip chain complexity, and decreases car use, but hardly alters activity patterns. The birth of a higher order child tends to increase men's car use, but not significantly.

For women, a first child strongly decreases the amount of paid work. It also reduces their number of trips and increases their car use, although both effects are only significant in the male model (for the female partners, respectively). A higher order child further decreases women's paid work, albeit to a lesser extent than a first child. Taken together, the birth of a child clearly affects women's activity patterns, but not men's. A first child seems to be associated with a certain shift in the use of the household car towards the mother.

In order to gain an impression of the magnitude of child birth effects on car use including indirect effects, total effects are reported, including both the models using percentages of car trips and the absolute number of trips driven (Table 2). Details for the model using trip numbers are available from the authors on request.

The total effect of child birth on men's car use is about as strong in magnitude as the direct effect. Men reduce the proportion of trips they drive by 18 percent (-0.18, direct effect b=-0.17) after the birth of a first child. This corresponds to an average decrease of 0.81 trips driven per day. After the birth of a second or further child they increase their car use by a mean 12 percent (+ 0.44 trips driven per day).

As outlined above, the total effects for women are weaker. After the first child is born, women increase their driving by 10 percent, while at the same time their number of trips driven decreases by 0.10 per day, indicating a relative shift towards driving, but a decrease in trip-making overall which may correspond to the decrease in paid work found above or/and out-of-home leisure. A higher-order child increases women's driving by 5 percent, corresponding to an increase of 0.37 in the absolute number of trips driven daily.

In households with two or more cars these effects are considerably different (Table 2). Compared to one-car couples, men in couples with two or more cars reduce their car use less after the birth of the first child (they even increase it in absolute terms, while the direct effect is still negative), and they increase it less after the birth of a further child. In other words: there is less change in mode use after child birth for men in multi-car couples. Women in multi-car couples do not increase, but rather decrease their car use in relative and absolute terms which corresponds to the overall decline in trip making noted above. This is especially true when they have a first child, less so for further children (total effect on change in number of trips: first child -0.85, further child -0.07 trips). Taken together, the results suggest that increases in driving are primarily an outcome of higher-order births, especially in one-car households.

Looking at standardised effects again (Table 3), it can be seen that changes in mode use are less pronounced in multi-car couples for both genders, in line with expectation. This refers to direct as well as total effects (including those mediated by other variables). An exception is the strong decline in the absolute number of trips driven by women after the first child's birth, which is associated with a strong decline in trip making (not shown in table).

**Table 2: Total effects of child birth on car use (unstandardised)**

| | Men | | Women | |
|---|---|---|---|---|
| | First child | Higher-order child | First child | Higher-order child |
| | **1 car households** | | | |
| % car trips | -0.18 | +0.12 | +0.10 | +0.05 |
| no. of car trips | -0.81 | +0.44 | -0.10 | +0.37 |
| | **2+ car household** | | | |
| % car trips | -0.07 | +0.02 | -0.17 | -0.00 |
| no. of car trips | +0.11 | +0.12 | -0.92 | -0.08 |

**Table 3: Total and direct effects of child birth on car use (standardised)**

| | Men | | Women | |
|---|---|---|---|---|
| | First child | Higher-order child | First child | Higher-order child |
| | **1 car households** | | | |
| Total effect | -0.08 | 0.05 | 0.05 | 0.03 |
| Direct effect | -0.08 | 0.06 | 0.06 | 0.04 |
| | **2+ car household** | | | |
| Total effect | -0.02 | 0.01 | -0.05 | -0.00 |
| Direct effect | -0.02 | 0.01 | -0.04 | 0.00 |

## 5 Conclusions

The paper reported on a multi-group path analysis that attempted to capture changes in car use over time. It is one of very few papers that build on a life-course perspective to travel while including interactions between two partners living in a household. It is also a rare case (in transport studies) of an analysis that addresses the order of children when looking at the effects of child birth. The analysis was categorised by the number of cars in a household, as changes in mode use were expected to be stronger in couples who share a car. The focus was on one-car couples. At the same time the model was subcategorised by gender, as earlier analysis showed that some changes over the life course affect men and women in different ways.

The results suggest multiple interactions between partners over time. These are negative with respect to driving (though only in one-car couples), but positive with respect to activity patterns. It was initially assumed that the links between activity patterns and car use were mediated by mobility patterns such as trip rates and trip-chaining behaviour, but the direct effects of changes in activity patterns on car use tend to be stronger than the indirect effects mediated by mobility patterns.

There seems to be a gender issue in the type of activity that affects car use. While increases in paid work enhance car use only for women, increases in unpaid work enhance car use for men. This suggests that individuals are successful in negotiating car access only if they increase those activities that are less typical for their own gender role.

With respect to child birth the main result is that the birth of a child clearly affects women's activity patterns, but not men's. On the other hand, the birth of a first child increases men's trip chain complexity, and decreases their car use so that a first child seems to be associated with a certain shift in the use of the household car towards the mother. Generally, increases in driving following the birth of a child seem to be primarily an outcome of higher-order births, especially in one-car households.

For households with two or more cars one may summarise as follows. In line with expectations, the birth of a child results in less change in mode use for men. However, contrary to expectation, comparatively strong changes for women were found in these households. Especially after the birth of a first child, women in multiple-car households decrease (rather than increase) their car use in relative and absolute terms which may correspond to the decline in trip making overall noted above.

Policy conclusions are not straightforward. Concerning child birth, there is a narrative in transport studies suggesting that child birth increases driving. One may conclude from this that founding a family is a moment in the life course when interventions to reduce driving (or reduce the increase in driving) may be warranted. The results presented here, however, suggest that increases in driving are primarily an outcome of higher-order births, and one may well doubt that there is much chance of keeping a noteworthy number of people with two or more children from driving. Hence, the idea that the birth of a child can be utilised as a 'window of opportunity' for policy may be overly optimistic.

The multiple intra-couple interactions found are another result which is relevant for policy, although both in a positive and a negative way. Positively, interactions in travel between people suggest that people may react to changes made by other people, particularly by close alters. This highlights the idea of social interventions in travel to create 'mass effects' (Abou-Zeid et al., 2013). Negatively expressed, exactly the same interactions may help explain why there is little change, as resistance to change may be a reflection of collective norms, mutual socialisation and inertia (Scheiner, 2018). In any case, the results strongly suggest to take social interactions between partners into account in policy concepts.

For future research, there is plenty to do when following the line of research proposed in this paper. Firstly, this paper focused on interactions within couples living in a household. Future studies could look at interactions between a wider range of family members and relatives within and outside the household over time (Ohnmacht, 2009; Plyushteva and Schwanen, 2018). Secondly, even though a number of (non-significant) variables such as activity pattern entropy were tested and excluded, such variables may play an important role in other contexts and when other travel behaviour measures are studied.

Thirdly, some of the results suggested intra-couple negotiations around the car, but the data did not allow such negotiations to be directly investigated. Looking at negotiations between partners, and perhaps also between parents and children, or other family members, may help to improve understanding of intra-family relationships and the role mobility plays in them. Especially qualitative work could increase researchers' understanding of how people create meaning around or 'make sense' of mobility and the ways mobility is embedded in and intertwined with other spheres of individual, couple, and family life over time.

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## Appendix – matrix of total standardised effects

| | Effect of… | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **MEN** | Paid work | | Unpaid work | | Car use | | Child birth (first) | Child birth (higher order) | Change in paid work | | Change in unpaid work | | Change in no. of trips | | Change in trip chaining | | Change in public transport to work | | Change in car use |
| Effect on… | R | P | R | P | R | P | HH | HH | R | P | R | P | R | P | R | P | R | P | P |
| R: Paid work | | 0.32 | | | | | | | | | | | | | | | | | | |
| R: Unpaid work | -0.30 | -0.03 | | 0.40 | | | | | | | | | | | | | | | | |
| P: Unpaid work | | -0.18 | | | | | | | | | | | | | | | | | | |
| R: Car use | 0.19 | -0.07 | 0.14 | -0.06 | | -0.23 | | | | | | | | | | | | | | |
| P: Car use | | 0.13 | | 0.07 | | | | | | | | | | | | | | | | |
| R: Change in paid work | -0.36 | -0.13 | | | | | -0.01 | 0.04 | | 0.05 | | | | | | | | | | |
| P: Change in paid work | | -0.34 | | | | | -0.20 | -0.07 | | | | | | | | | | | | |
| R: Change in unpaid work | 0.09 | -0.02 | -0.60 | -0.30 | | | -0.02 | -0.01 | -0.17 | -0.01 | | 0.32 | | | | | | | | |
| P: Change in unpaid work | | 0.00 | | -0.64 | | | -0.01 | 0.01 | | -0.12 | | | | | | | | | | |
| R: Change in no. of trips | -0.01 | -0.02 | -0.12 | -0.09 | | | -0.04 | 0.00 | 0.05 | 0.00 | 0.20 | 0.11 | | 0.18 | | | | | | |
| P: Change in no. of trips | | -0.02 | | -0.17 | | | -0.09 | 0.00 | | 0.01 | | 0.26 | | | | | | | | |
| R: Change in trip chaining | 0.00 | 0.00 | 0.01 | -0.04 | | | 0.04 | 0.00 | 0.01 | -0.01 | -0.01 | 0.06 | 0.05 | 0.05 | | 0.80 | | | | |
| P: Change in trip chaining | | 0.00 | | -0.07 | | | -0.02 | 0.00 | | -0.01 | | 0.11 | | 0.05 | | | | | | |
| R: Change in car use | -0.06 | 0.03 | -0.13 | -0.01 | -0.35 | 0.11 | -0.08 | 0.05 | 0.00 | -0.01 | 0.13 | 0.03 | 0.04 | -0.07 | -0.01 | 0.00 | 0.05 | 0.00 | -0.10 |
| P: Change in car use | | -0.08 | | 0.00 | | -0.34 | 0.04 | 0.03 | | 0.12 | | -0.04 | | 0.00 | | -0.05 | | 0.03 | |

| | Effect of… | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **WOMEN** | Paid work | | Unpaid work | | Car use | | Child birth (first) | Child birth (higher order) | Change in paid work | | Change in unpaid work | | Change in no. of trips | | Change in trip chaining | | Change in public transport to work | | Change in car use |
| Effect on… | R | P | R | P | R | P | HH | HH | R | P | R | P | R | P | R | P | R | P | P |
| R: Paid work | | 0.32 | | | | | | | | | | | | | | | | | |
| R: Unpaid work | -0.24 | 0.04 | | 0.43 | | | | | | | | | | | | | | | |
| P: Unpaid work | | -0.26 | | | | | | | | | | | | | | | | | |
| R: Car use | 0.09 | 0.21 | 0.14 | -0.08 | | -0.17 | | | | | | | | | | | | | |
| P: Car use | | 0.07 | | 0.06 | | | | | | | | | | | | | | | |
| R: Change in paid work | -0.37 | -0.14 | | | | | -0.20 | -0.06 | | 0.07 | | | | | | | | | |
| P: Change in paid work | | -0.35 | | | | | 0.00 | 0.04 | | | | | | | | | | | |
| R: Change in unpaid work | 0.04 | -0.06 | -0.60 | -0.29 | | | 0.00 | 0.01 | -0.12 | 0.01 | | 0.36 | | | | | | | |
| P: Change in unpaid work | | 0.04 | | -0.64 | | | -0.02 | -0.01 | | -0.15 | | | | | | | | | |
| R: Change in no. of trips | -0.01 | -0.03 | -0.15 | -0.10 | | | -0.08 | 0.00 | 0.03 | 0.01 | 0.26 | 0.13 | | 0.17 | | | | | |
| P: Change in no. of trips | | -0.01 | | -0.14 | | | -0.04 | 0.00 | | 0.03 | | 0.22 | | | | | | | |
| R: Change in trip chaining | 0.00 | 0.00 | -0.02 | -0.05 | | | -0.02 | | 0.00 | -0.01 | 0.04 | 0.08 | 0.01 | 0.07 | | 0.77 | | | |
| P: Change in trip chaining | | 0.00 | | -0.02 | | | 0.05 | | | 0.00 | | 0.03 | | 0.09 | | | | | |
| R: Change in car use | -0.07 | -0.08 | -0.04 | 0.06 | -0.31 | 0.10 | 0.05 | 0.03 | 0.11 | 0.01 | -0.02 | -0.05 | 0.03 | -0.14 | -0.05 | -0.04 | 0.03 | 0.03 | -0.12 |
| P: Change in car use | | -0.02 | | -0.11 | | -0.36 | -0.08 | 0.05 | | -0.03 | | 0.14 | | 0.06 | | -0.01 | | 0.06 | |

R: Respondent, P: Partner, HH: Household.