Life course changes in travel mode use with partner interactions

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Abstract

The paper links two strands of research on travel behaviour, i.e. the mobility biographies literature and the literature on intra-household interactions in travel. It studies changes in car use from one year to the next as a function of life events (namely the birth of a first-order or higher-order child), changes in household worksharing with respect to paid and unpaid work, and trip patterns. In doing so, it does not only take into account changes in the respondents' variables, but also changes in partner variables. The analysis focuses on dual-licenced couple households sharing a car. This is based on the expectation that changes in mode use are most likely among those who share a car and, thus, may need to renegotiate car access when change occurs. The data used is the German Mobility Panel 2004 to 2016. At the time of submission this is work in progress. Hence, results are not yet available. Interim results suggest that multiple interactions between partners can be observed.

Keywords: mobility biography, life course, travel behaviour change, car use, mode choice

1 Introduction

The past fifteen years have seen a tremendous increase in research on travel behaviour change. This includes studies about short-term, day-to-day variability as well as longer-term change. The interest has been motivated, on the one hand, by the evaluation of initiated travel demand management programmes for change, such as personalised travel planning (Skarin et al., 2017), or effects of infrastructure provision (Cao and Ermagun, 2017) that attempt 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.

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), and Plyushteva and Schwanen (2018) highlight the diversity of shorter and longer-term, gradual and abrupt temporalities that interfere with each other. 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 events and changes a person experiences, on their partner's or family's travel (but see Plyushteva and Schwanen, 2018; Rau and Sattlegger, 2017). A recent review of mobility biographies studies can be found in Scheiner (2018).

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 two decades. It is arguably at least as wide as the life course approach, and involves multiple facets of both social networks and travel dimensions. A basic distinction can be made between studies that look at interactions in travel between members of the same household (intra-household interactions) (see Ho and Mulley, 2015; Kroesen 2015), and studies on the links between (out-of-household) social networks and travel (see Kim, Rasouli and Timmermans, 2017; Goetzke et al., 2015; for family networks beyond the household see Rau and Sattlegger, 2017; for wider social influences Sherwin et al., 2014).

Yet linking the two fields – mobility biographies and intra-personal interactions in travel – is an undertaking that remains to be done. Early conceptual work on mobility biographies (Lanzendorf, 2003; Scheiner, 2007) included the household and family context, but with little emphasis on working out the details of intra-household interaction. 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.

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. 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 typically based on mean estimations. Little has been done to date in this respect using standardised data. None of the empirical work using standardised data focuses exclusively on intra-household interactions.

This paper does exactly this. It 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 respondents and their partners. Gradual changes also include the two partners' individual activity and travel patterns.

2 Data and methodology

2.1 Data

The analysis presented in this paper makes use of the German Mobility Panel (GMP) 2004 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 2004-2006, 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. 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.

The GMP has a number of advantages over other data sources that suit the purpose of this paper. First, 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. Second, the GMP allows the inclusion of rich information about mobility and access, e.g. to detect associations between time use and car use. Third, the GMP is a long-standing panel survey with only marginal change in survey methods and, hence, strong consistency of data over time.

[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).

On the other hand, activity categories are rather coarse, and thus differ from time use diaries. Coding multiple 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 but sharing a car as we assume less effect on car use of life course changes among dual-car couples. From previous research it may be expected that some effects of changes on car use differ between men and women (Scheiner, 2014). Hence we employ multi-group models to test for gendered effects.

The data include a total of 3,400 individual weeks of report after accounting for missing data.

2.2 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 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. 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).

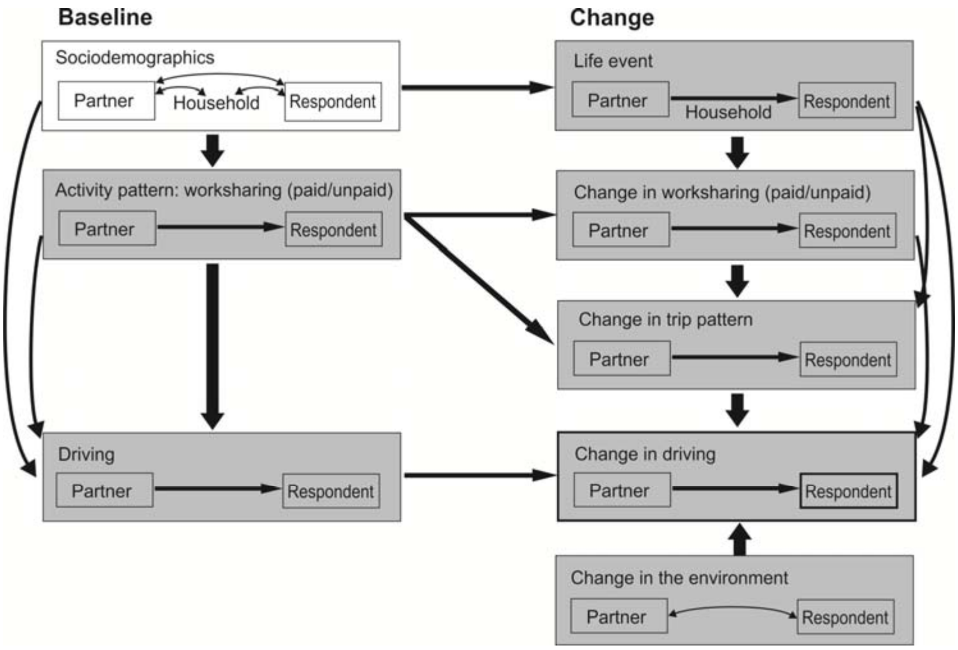

Figure 1: Model structure

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

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.

2.3 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 standard estimator for SEM is Maximum Likelihood (ML), but this estimator requires multivariate 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.

2.4 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 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.

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. 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).

2.5 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).

3 Results

3.1 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 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 based on the same data with considerably more variables, but less complexity in model structure (19.3 percent - women, and 22.4 percent - men, Scheiner, 2014).

		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			

Table 1: Descriptives of the variables used

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

3.2 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.

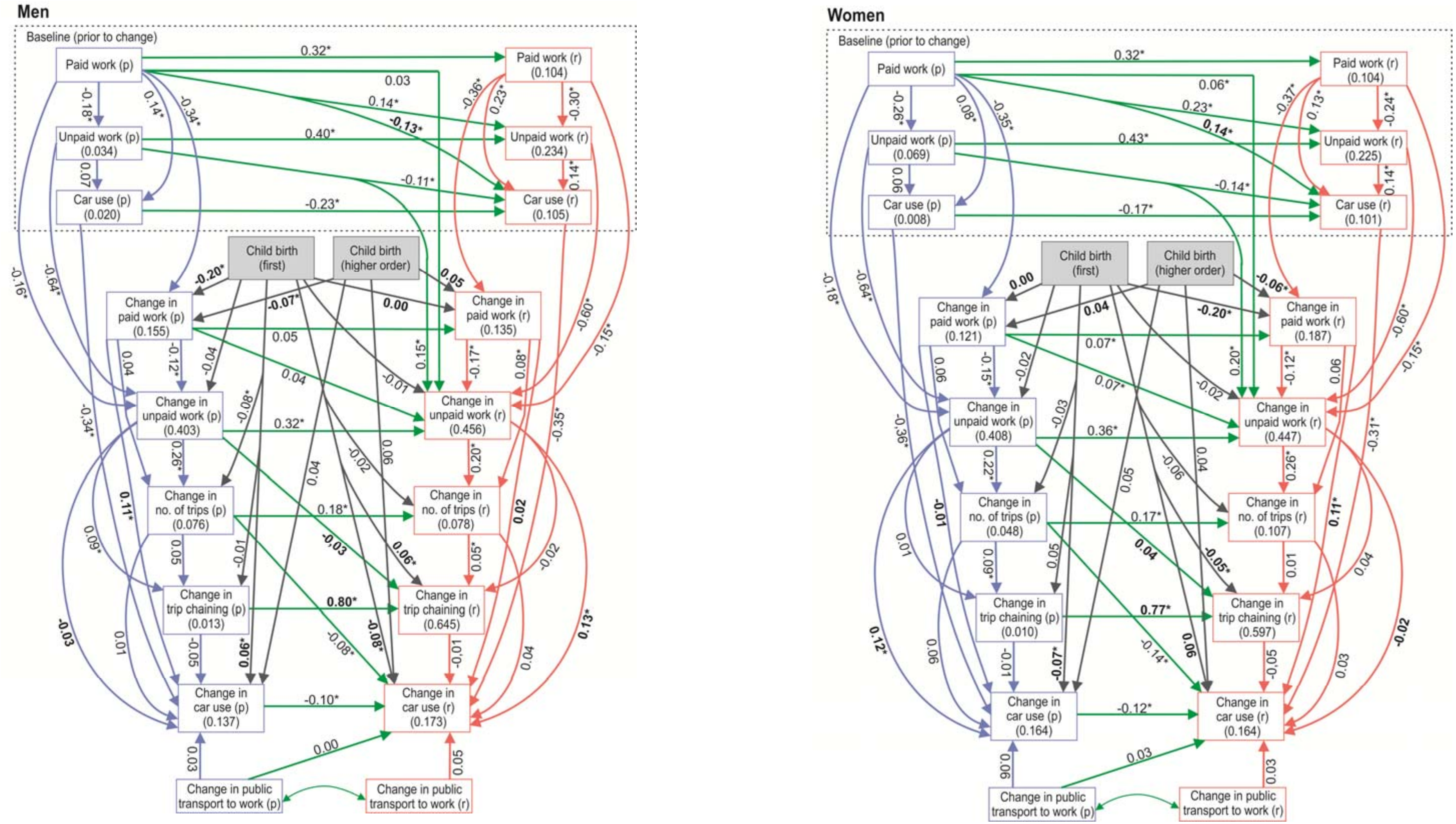

Figure 2: Final path model of change in driving

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.

3.2.2. 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.

3.2.3. 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.

3.2.4. 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.

3.2.5. 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.

	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 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			
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

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

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).

4 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 focus was on one-car couples. At the same time the model was subcategorised by gender. 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.

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. 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, the birth of a child results in less change in mode use for men, while 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 a decline in trip making overall.

Future studies could look at interactions between a wider range of family members and relatives within and outside the household over time. 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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