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A dynamic approach to long term mobility decisions in the life course

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ABSTRACT

The relatively new research field of mobility biographies designates the analyses of long-term mobility behaviour and the availability of mobility tools in a life span. A retrospective survey of the TU Dortmund, ETH Zurich and Goethe University Frankfurt collects data on individual mobility biographies of three different generations in a household with a life-calender. Most of the past long-term decisions made by individuals such as buying a house or changing job affect their preferences in future periods and induce economic constraints in the form of transaction costs. Ignoring these aspects may lead to biased estimated in the analysis. A dynamic probit model is used to identify impacts on the individual decisions on car availability in a life span and tests for differences between gender or is used to include the time dependency of the explanatory variables such as age, the number of children or education. The focus of the paper is to compare the modelling results following common practices in the life course calendar literature, based on random effects probit models with the results obtained with a dynamic random effects probit model with autocorrelation. In contrary to the classic random effects probit model approach the main advantage of the dynamic probit approach is to explicitly model the correlated time-fixed and time-varying unobserved heterogeneity.

INTRODUCTION AND RELATED WORK

The contemporary increasing complexity of household and family structures, labour markets changes and individualisation of lifestyles cohere with an increase in activities and flexibility, changing attitudes and behaviour patterns. This also affects individual mobility behaviour as well as mobility tool ownership. It is still challenging to capture such ideas conceptually, methodically and empirically, and to identify the most influential factors in order to contribute to planning practice *(1)*. So far changes in mobility behaviour are often covered with static cross-sectional studies but these neglect the dynamic and implications of long term decisions *(2)*.

In the past decade the focus of interest therefore shifted towards individual and joint long term decisions in a life span. The biography approach examines mobility behaviour (including residential choice and travel behaviour) in the context of key events in a life course (such as changes of job or family formation) and life phases (e.g. adolescence or the family phase). Besides people's own experiences the influence of the social environment is of interest. The relevance of both the life course and the social environment are acknowledged in the theoretical discussions about mobility biography and mobility socialisation *(3)*. *(4)* show that strong interdependencies exist between the various key events and long-term mobility decisions during the life course and argue that events occur to a great extent simultaneously.

Several empirical studies attempt to understand and explain everyday travel behaviour as a routine activity changing due to key events such as residential relocation, the birth of a child or exogenous interventions. A comprehensive review of the theoretical framework and most important studies investigating mobility behaviour and mobility tool ownership over the life course has been recently published by *(5)*. The authors address open research questions and conclude that studies often investigate long-term decisions with static (panel) models and neglect the dynamic, causality, interraltaions and time dependency of the target and explanatory variable *(5)*.

This paper introduces a new approach for a dynamic probit model trying to take the earlier described dependencies into account. The framework of the model is explained in the following section *Modelling approach* which is subsequently applied to empirical data of a retrospective survey. The paper continues with the description of the data set used for the application in the section *Data description*. The model results are presented and discussed in the section *Results*. The Section *Conclusions and Outlook* summarizes this paper and gives an outlook on future work and challenges.

MODELLING APPROACH

As previously introduced, the standard modelling approach for analysing transportation mode availability over the life course revolves around static *random-effects (RE) panel probit models*. Yet, in many cases, and in particular when investigating the determinants of car availability, the outcome probability is likely to depend on the outcome in the previous period. Car availability for a given individual during time period t is likely to influence the decision of having or maintaining a car available during time period $t + 1$. Accounting for such effect, known as state dependence, renders the *standard RE probit model* estimator inconsistent *(6)*. Indeed, in such context, estimations can be biased when ignoring individual-specific effects. In the literature, the problem is generally solved by including a time-invariant error term. However, this term might be correlated with the initial conditions and, as a result, endogenous. This problem is referred to as the "initial condition problem" (e.g. *(7)*;*(6)*; *(8)*). Yet, the *Heckman estimator* is inconsistent if the error terms are autocorrelated *(8)*. In the literature, several estimations techniques have attempted to address these issues as summarized by *(9)*. Recently, *(8)* has introduced a *Maximum Simulated Likelihood (MSL) estimator* for the *RE dynamic probit model* with autocorrelated errors. In this section, we only report the most salient features of this modelling approach and give extensive details on how it can be used in order to investigate the dynamics of car availability. The complete model description is available from *(8)*.

A dynamic random-effects probit model with autocorrelated errors

(8) introduces the dynamic random-effects probit model with autocorrelated errors as such: A latent variable y^*_{it} is specified for t (with $t \geq 2, \ldots, T$) by

$$y^*_{it} = \gamma y_{it-1} + x^{'}_{it}\beta + \alpha_i + u_{it} \tag{1}$$

(8) describes the outcome variable y_{it} as equal to 1 if $y^*_{it} > 0$ and 0 else. $i = 1, \ldots, N$ corresponds to the individuals and t corresponds to the time periods. The right hand side of the equation is described as follows: y_{it-1} is the lagged dependent variable, $x^{'}_{it}$ are the exogenous regressors, α_i is a time-invariant error term that is uncorrelated with the explanatory variables. It is assumed to be independently and identically distributed ($\alpha_i \; N(0, \sigma^2_\alpha)$). u_{it} is the time-specific, idiosyncratic, error term. It is assumed to follow a standard normal distribution ($u_{it} \; N(0, 1)$). The composite error term is described as

$$\upsilon_{it} = \alpha_i + u_{it} \tag{2}$$

It is always correlated over time because it integrates α_i. The equicorrelation structure between the υ_{it} over any two different time periods corresponds to

$$Corr(\upsilon_{it}, \upsilon_{is}) = \sigma^2_\alpha \tag{3}$$

with $t, s = 2, \ldots, T$ and $t \neq s$. Besides, υ_{it} may be assumed to be autocorrelated and, in such case, follow a first-order autoregressive process so that

$$\upsilon_{it} = \delta u_{it-1} + \epsilon_{it} \tag{4}$$

(8) follows *(10)* and estimates a static equation for the first time-period which corresponds to

$$y^*_{i1} = z^{'}_{i1}\pi + \epsilon_i \tag{5}$$

z_{i1} contains the set of explanatory variables referred to as x_{it} above as well as one or several exogenous instrumental variables that only have an effect on the outcome in the first period. *(8)* assumes that α_i is correlated with the error term in the initial period, which gives

$$\epsilon_{it} = \theta\alpha_i + u_{i1} \tag{6}$$

With u_{i1} $N(0, 1)$. Finally, the correlation of the composite error terms between $t = 1$ and $t > 1$ simply corresponds to

$$Corr(\epsilon_{it}, \upsilon_{is}) = \theta\sigma_\alpha^2 \tag{7}$$

(8) then follows the approach of *(11)* and apply a multivariate probit model. It is worth noting that in the model suggested by *(8)*, the number of individuals N is taken to be large while the number of time periods T is smaller and considered as fixed so that asymptotics are on N alone. We highlight that this may cause inconsistencies in the case where the life course calendar data collection covers an extended period of time. In the remainder of this paper, T varies depending on individuals and goes up to 32. While in this paper we follow the specification proposed by *(8)* and compare it to the standard RE probit approach, we acknowledge the existence of other methods that are well suited for longer life course calendar data such as the Efficient Importance Sampling methodology developed by *(12)* and also used by *(13)*. Our future applications of the dynamic random-effects probit model for analysing car availability over the life course will include a comparison of these different approaches. We now describe how the approach proposed by *(8)* is applied to describe the dynamics of car availability over the life course.

Car availability over the life course

Car availability over the life course is a well suited topic to test the properties of the dynamic RE probit model approach proposed by *(8)*. Indeed, as previously stated, there are strong assumptions that car availability implies a strong degree of state dependency. Car availability is not only a choice of mode of transport but has a strong influence on job and residential location choice. The decision to have a car available has been found to be associated with life events. For example, *(14)* identified that a change in the number of household members, the birth of the first child, relocation or a change in the monthly income are events that all have an influence on car availability. Moreover, on a study on state dependence associated with car ownership, *(15)* argue that true state dependence may be related to past car ownership having impacts on preferences as well as economic constraints in the form of transaction costs related to buying and selling a car. *(16)* reports the same findings and states that car ownership is clearly associated with habit and resistance to change and that it is difficult to abandon even if the economic consequences of having a car available may not evolve favourably for the owner. These findings also underline that the use of dynamic models for investigating car availability or car ownership is not a novelty.

Yet, it is the first time to our knowledge that such models are applied to analyse data obtained by the mean of life course calendar survey. Previous attempt to use dynamic models for analysing car availability or car ownership have either focused on microeconomic panel data, merging different data registries or pseudo-panel data obtained by the mean of consumption surveys (see *(16)* for example).

On the other hand, life course calendar data have been often analysed by the mean of static random effect models, thus ignoring the potential effects of state dependency. As previously stated, this paper aims at conciliating the richness of the insights provided by life course calendar data, as argued in the previous section together with the behavioural realism brought by accounting for state dependency in discrete choice models.

DATA DESCRIPTION

The data originates from a retrospective survey which is carried out since 2007 at a the Department of Transport Planning of the TU Dortmund as an annually first-year seminar's homework. The questionnaire for the survey was primary designed as part of a diploma thesis *(17)* and has been used since then without adjustments to guarantee the comparability of the data. Since 2012 it is part of the collaborative project *"Mobility Biographies: A Life-Course Approach to Travel Behaviour and Residential Choice"* and data is additionally collected in Frankfurt and Zurich.

The survey addresses the students of the seminar, their parents and grandparents. The students represent the seeds and are asked to give the questionnaire to both their parents and two of their grandparents - who are randomly chosen, one from the maternal and one from the paternal side. If one of the family members is not available for any reason the students can alternatively ask another person preferably of the same generation. The questionnaire which is the same for every generation asks for retrospective information on an individual's residential and employment biography, travel behaviour and holiday trips as well as socio-economic characteristics and behavioural attitudes.

From 2007 - 2012 the participation in the survey was mandatory for the students in Dortmund which hence resulted in an average response rate above 90%. In 2013 the students could participate voluntarily thus the rate dropped to almost 20% which is slightly higher but still comparable to the response rates experienced in Frankfurt and Zurich in 2013 where participation was also voluntary. Consequently since 2014 the data collection is again mandatory in Dortmund and also in Frankfurt. Due to university ethical guidelines participation in Zurich remains voluntarily. The data is collected on person level so that every individual represents one case in the dataset. It is also possible to identify the members of one family and model aggregated groups.

Data issues

As the sample has a unique structure it is not possible to appraise representativeness (see *(18)* or *(19)* for problems with representativeness in snowball surveys). The seeds are participants of a university seminar thus due to survey design highly educated individuals are likely to be overrepresented in all three generations. The majority of the respondents live in Dortmund respectively North Rhine-Westphalia - one of the most densely populated regions of Germany - so the data might also contain a bias to a more urban population. Furthermore within the grandparent generation a bias to female participants who live longer on the one hand and are also often younger, more popular and communicative can be recognized *(20)*. Finally retrospective data especially collected for a long period as the life course always bears the risk of the so called memory bias which means a unintended or voluntary bias of the autobiographic memory *(21)*. However the whole study focusses on mobility behaviour in the life-course and on finding intergenerational relations thus the results are not expected to be significantly affected by the structural differences between the sample and the population. Are more detailed documentation of the data set can be found in *(20)*

Model specification

For this paper data gathered in Dortmund from 2007-2012 is analysed. The dataset contains 960 families. As described before each survey family consists of up to five persons of three generations. In the grandparents generation 1294 (812 female and 482 male) individuals answered the questionnaire. The parents generation contains 1787 (926 female and 861 male) individuals. 585 individuals are unrelated persons (e.g. friends, siblings or neighbours). The youngest generation in the dataset is represented by the seeds - the students (954 individuals). For the modelling approach of this paper only the respondents of the parents generation where chosen. Due to calculation run time limitation the sample has been reduced to a 25% sub-sample of the 1787 individuals of the parent generation and for the years from 1980 to 2012. The according time interval therefore is 32 years where each year represents a case for each individual.

As previously introduced, the model is composed of a static equation for the first time period and a dynamic equation when $t > 1$. The variables entering the equation for the initial period are:

- car: car availability per year, dependent variable
- age: age in the corresponding year
- s_age100: Square of age / 100
- $german$: German Nationality yeas = 1, no = 0
- $degree$: University degree yes = 1, no = 0
- $distw$: distance to work in the corresponding year
- $s\_distw100$: Square of distw / 100
- $children$: number of children in the corresponding year
- mar_status: marriage status in the corresponding year, married = 1, divorced/single = 0
- $license\_moped$: driver's license moped yes = 1, no = 0
- $license\_car$: driver's license car yes = 1, no = 0
- $gender$: included as an instrument because it is found to be negative and significant in the first time period but not in the subsequent ones

The variables of the previous equation remain the new variable entering when $t > 1$ is:

- car_{t-1}: Lagged car availability variable. It is equal to 1 when there is a car available at $t-1$ and 0 else

The number of periods observed per individual varies, as expected in the life course calendar literature. Here, the minimum number of time periods observed is 31 while the maximum is 32. In order to help convergence, two probit models, one for $t = 1$ and one for $t > 1$ have been estimated in order to obtain feasible starting values as recommended by *(8)*. These models are not reported in the paper but are available from the author upon request.

Table 1 provides a descriptive overview of the socio-economic variables used for modelling.

TABLE 1 Socio-economic charateristics

Attribute	No of obs.	Percent	Mean	Std.dev.	Min	Max
Car available						
No	1124	13%	–	–	–	–
Yes	7745	87%	–	–	–	–
Age	8869	100%	37.65	9.79	18	68
German citizen						
No	279	3%	–	–	–	–
Yes	8590	97%	–	–	–	–
University degree						
No	4947	56%	–	–	–	–
Yes	3860	44%	–	–	–	–
Don't say	62	1%	–	–	–	–
Distance to work	8869	100%	12.24	21.87	0	420
Number of children	8869	100%	1.57	1.28	0	9
Marriage status						
Single/Divorced	2227	25%	–	–	–	–
Married	6642	75%	–	–	–	–
License moped						
No	6369	72%	–	–	–	–
Yes	2500	28%	–	–	–	–
License car						
No	946	11%	–	–	–	–
Yes	7923	89%	–	–	–	–
Gender						
Male	4542	51%	–	–	–	–
Female	4327	49%	–	–	–	–

RESULTS

In this section, we compare the results obtained from the *dynamic RE probit model* with state dependence (model a) which are shown in Table 2 with the results obtained from the *RE probit model* usually used in the life course calendar literature (model b) which are shown in Table 3.

We find that accounting for state dependence, autocorrelation and initial condition in addition to random-effects has a considerable effect on the explanatory power of the model and the conclusions that can be derived from it. First of all, the variable $LCar$ is found to be significant with a strong, positive effect. As previously found in the literature, our results show strong support for the fact that car availability may induce state dependency. In line with what has been found by *(22)*, moving from the *RE probit model* to the *dynamic RE probit* with state dependence and autocorrelation greatly reduce the size as well as the significance of age effects in comparison to the coefficients of model a for periods that correspond to $t > 2$.

TABLE 2 Model results dynamic RE probit

	Coef.	Std. Err.	z	$P > z$	95% CI
Later					
Lcar	3.338	0.213	15.660	0.000	2.920 ; 3.756
s_age100	-0.068	0.070	-0.970	0.334	-0.205 ; 0.070
age	0.067	0.056	1.190	0.236	-0.044 ; 0.177
deutsch	0.187	0.566	0.330	0.741	-0.922 ; 1.295
degree	0.004	0.154	0.030	0.979	-0.298 ; 0.306
s_distw100	-0.005	0.002	-2.060	0.039	-0.010 ; 0.000
distw	0.020	0.007	3.000	0.003	0.007 ; 0.033
children	-0.082	0.089	-0.920	0.357	-0.257 ; 0.093
mar_status	0.041	0.184	0.220	0.825	-0.320 ; 0.402
license_moped	0.593	0.325	1.820	0.068	-0.044 ; 1.231
license_car	2.169	0.368	5.890	0.000	1.447 ; 2.890
cons	-3.453	1.100	-3.140	0.002	-5.608 ; -1.298
Initial Period					
s_age100	-1.416	0.759	-1.870	0.062	-2.904 ; 0.072
age	0.824	0.376	2.190	0.029	0.086 ; 1.561
deutsch	-1.697	0.954	-1.780	0.075	-3.568 ; 0.174
degree	0.195	0.204	0.960	0.339	-0.205 ; 0.595
s_distw100	-0.023	0.012	-1.910	0.056	-0.047 ; 0.001
distw	0.099	0.037	2.630	0.008	0.025 ; 0.172
children	-0.188	0.315	-0.600	0.551	-0.806 ; 0.430
mar_status	-0.570	0.551	-1.030	0.301	-1.649 ; 0.510
license_moped	1.179	0.471	2.500	0.012	0.256 ; 2.102
license_car	2.879	0.615	4.680	0.000	1.674 ; 4.084
gender	0.491	0.304	1.620	0.106	-0.104 ; 1.087
cons	-12.181	4.494	-2.710	0.007	-20.990 ; -3.373
$Sigma^2$	1.846	.617	2.99	0.003	.958 ; 3.554
Theta	1.006	.279	3.61	0.000	.585 ; 1.732
trho	.186	.166	1.12	0.263	-.148 ; .481
Number of obs	=	8869			
Wald chi2(11)	=	409.47			
Prob > chi2	=	0.0000			
Log likelihood	=	-481.61664			

Surprisingly, the effect of *children* and *mar_status* have not been found to be significant for both specifications, which differs from the results usually obtained in the literature. Moreover, the variable *German* is not found to be significant in model b and in model a. Yet, it is found to be significant in the initial period model.

Moving to the set of variable that are more typically found in the life course calendar literature, we observe that the variables *distw* are significant and positive for both model

TABLE 3 Model results RE probit

Car	Coef.	Std. Err.	z	$P > z$	95% CI
s_age100	-0.425	0.049	-8.720	0.000	-0.521 ; -0.330
age	0.370	0.041	9.100	0.000	0.290 ; 0.450
deutsch	0.140	2.770	0.050	0.960	-5.289 ; 5.568
degree	-0.020	0.212	-0.100	0.923	-0.437 ; 0.396
s_distw100	-0.009	0.002	-4.280	0.000	-0.014 ; -0.005
distw	0.037	0.007	5.550	0.000	0.024 ; 0.050
children	0.048	0.085	0.570	0.571	-0.119 ; 0.215
mar_status	0.061	0.143	0.430	0.669	-0.219 ; 0.342
license_moped	1.389	0.498	2.790	0.005	0.413 ; 2.365
license_car	4.794	0.692	6.930	0.000	3.439 ; 6.150
central	0.173	0.042	4.140	0.000	0.091 ; 0.254
gender	1.257	0.491	2.560	0.011	0.293 ; 2.220
cons	-10.173	3.510	-2.900	0.004	-17.053 ; -3.293
lnsig2u	2.695	0.151			2.399 ; 2.991
sigma_u	3.848	0.290			3.319 ; 4.461
rho	0.937	0.009			0.917 ; 0.952
LL-ratio test rho=0 chibar2(01)	=	*3363.45*			
Prob>=chibar2	=	*0.000*			
Number of obs	=	8621			
Number of groups (id)	=	277			
RE u_i Gaussian					
Obs per group min	=	31			
Obs per group avg	=	31.1			
Obs per group max	=	32			
Wald chi2(11)	=	379.53			
Prob > chi2	=	0.0000			
Log likelihood	=	-856.02358			

specifications. However, the effect of the variable in the *RE probit model* is much higher than the value found in dynamic model a. The same result is found for *s_distw100*, which is found to be negative and significant in both cases but with a much higher coefficient in model *RE probit model* in comparison to the *dynamic RE probit model*.

License_moped and *License_car* are also both found to be positive and significant for both models. Yet, again, the use of a different specification for the models renders this effect much smaller in the dynamic model. The instrument gender, which has been selected on the basis of previous analysis, is not found to be significant at the 10% level. However, the variable is very close to this threshold ($P > |Z| = 0.106$). The estimated models included the parents generation and observations of a time interval from 1980 to 2012. It can be assumed that gender has a stronger impact in the grandparents generation as it was seen in other analyses of the data (e.g.*(23)*. Furthermore until the 1990s an increase in car use and auto-mobile access for all age groups together with diminishing gender differences could be recognized in Germany *(24)*. However, further modelling attempts with the full dataset are expected to show a significant gender effect.

Fit measures are compared for both models. For model a, the log-likelihood is found to be −481.616, while it is −889.441 for model b. Besides, the AIC measure for model a corresponds to 1017.233 while it is 1804.883 for model b. It is hence found that the *dynamic RE probit model* with autocorrelation outperforms the *RE probit* in terms of goodness-of-fit.

We now provide results regarding the dynamic aspects of the *RE probit model*. First of all, we find that the estimated variance of α_i is found to be significant and positive. Hence, the time-invariant error term is found to be different from θ for the time periods $t > 1$. Moreover, we find that α_i is correlated with the initial conditions because θ is found to be significantly positive and different from θ. As a result, exogeneity of the initial conditions must be rejected, in contrary of the assumptions of the *RE probit model* which assumes it.

Finally, the hypothesis of no autocorrelation cannot be rejected which implies that the successive realisations of u_{it} are not significantly correlated. Overall, these results give strong support to the use of a *dynamic RE probit* approach in comparison to the standard *RE probit* for modelling life course calendar data in the sense that ignoring these aspects may have led to biased estimates. These results suggest that the use of *dynamic RE probit model* with autocorrelation and state dependence may improve the econometric result derived from life course calendar data in comparison to the standard econometric techniques in use.

CONCLUSIONS AND OUTLOOK

This paper analysed the determinants of household car availability in Germany since 1980 using data from a life course calendar survey that took place in Dortmund between 2007 and 2012. Car availability is a common focus in the life course calendar literature and understanding the dynamics of car availability and, on a broader context, of mobility and mobility tool choice is crucial for policy design. In contrary to similar approaches on the same topic, our data cover an extensive period of time because of the use of a life course calendar approach for collecting data (up to 32 years per individual, from 1980 to 2012). A particular focus of the paper was to compare the modelling results that are obtained following common practices in the life course calendar literature, based on *RE probit models*, with the results obtained with more recent econometric approaches such as the *dynamic RE probit model* with autocorrelation proposed by *(8)*.

In this paper we have introduced the dynamic probit model to the examination of the life course, and the initial results are such that this approach shows great promise as a method. In particular, we first suggest to extend the use of the dynamic RE probit model with autocorrelation to model a wider range of choices that are of interest in the life course calendar literature.

Future versions of this paper will include the analysis of different life course events such as relocation, job change or bus seasonal ticket ownership. Besides, models will be estimated for three successive generations of Germans. Moreover, models could be estimated for the complete sample rather than for a smaller subset, which has not been possible yet because of the time required to estimate the model (from 30 hours up to weeks depending on the model specification).

Future versions of this paper will also include attempts to reduce the computational cost of estimating the dynamic models as well as a comparison of the results obtained with the estimator used in the current paper with those obtained using the *Efficient Importance Sampling methodology* developed by *(12)*, which may be better suited for analysing life course calendar data. Finally, it has not been possible in this paper to introduce an in-depth analysis of income effect and family effects on car availability. However, future estimates will investigate these elements too.

The dynamic probit approach may be seen as a superior alternative in the context of analysing car availability and, in a broader context, life course events for the main reason that it accounts for state dependency. Hence, adopting a dynamic approach consists in asking whether car availability status in past periods affects present car availability. We argue that state dependency is a very important aspect to consider in the context of life course calendar analysis in the sense that most of the past long-term decisions made by individuals such as buying a house or changing job affect their preferences in future periods and induce economic constraints in the form of transaction costs as previously stated. Ignoring these aspects may lead to biased estimated. In addition, the dynamic approach allows to model the initial conditions as endogenous, which prevent the estimators to be inconsistent. More generally, the main advantage of the dynamic probit approach is to explicitly model the correlated time-fixed and time-varying unobserved heterogeneity, in contrary to the classic RE probit model approach.

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REFERENCES

1. Axhausen, K. W. (2008) Social networks, mobility biographies, and travel: Survey challenges, *Environment and Planning B*, **35** (6) 981–996.

2. Lanzendorf, M. (2003) Mobility biographies: A new perspective for understanding travel behaviour, paper presented at the *10th International Conference on Travel Behaviour Research (IATBR)*, Lucerne, August 2003.

3. Scheiner, J. (2007) Mobility biographies: Elements of a biographical theory of travel demand (mobilitätsbiographien: Bausteine zu einer biographischen theorie der verkehrsnachfrage), *Erdkunde*, 161–173.

4. Beige, S. and K. W. Axhausen (2012) Interdependencies between turning points in life and long-term mobility decisions, *Transportation*, **39** (4) 857–872.

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

6. Stewart, M. (2006) Maximum simulated likelihood estimation of random-effects dynamic probit models with autocorrelated errors, *The Stata Journal*, **6** (2) 256–272.

7. Heckman, J. J. (1981) The incidental parameters problem and the problem of initial conditions in estimating a discrete time-discrete data stochastic process., *The MIT Press*.

8. Plum, A. et al. (2014) Simulated multivariate random effects probit models for unbalanced panels, *The Stata Journal*, **14** (2) 259–279.

9. Gao, W., W. Bergsma and Q. Yao (2014) Estimation for dynamic and static panel probit models with large individual effects, *arXiv preprint arXiv:1409.7776*.

10. Heckman, J. J. (1981) Heterogeneity and state dependence, in S. Rosen (ed.) *Studies in labor markets*, vol. 31, 91–140, University of Chicago Press, Chicago.

11. Cappellari, L. and S. P. Jenkins (2006) Calculation of multivariate normal probabilities by simulation, with applications to maximum simulated likelihood estimation, *The Stata Journal*, **6** (2) 156–189.

12. Richard, J.-F. and W. Zhang (2007) Efficient high-dimensional importance sampling, *Journal of Econometrics*, **141** (2) 1385–1411.

13. Liesenfeld, R., G. valle Moura and J.-F. Richard (2007) Dynamic panel probit models for current account reversals and their efficient estimation, *SSRN Working Paper Series*.

14. Prillwitz, J., S. Harms and M. Lanzendorf (2006) Impact of life-course events on car ownership, *Transportation Research Record*, **1985**, 71–77.

15. Bjørner, T. B. and S. Leth-Petersen (2005) Dynamic models of car ownership at the household level, *International Journal of Transport Economics*, 57–75.

16. Dargay, J. M. (2001) The effect of income on car ownership: evidence of asymmetry, *Transportation Research Part A: Policy and Practice*, **35** (9) 807–821.

17. Klöpper, V. and A. Weber (2007) Generationsübergreifende Mobilitätsbiographien, Master Thesis, Faculty of Spatial Planning, Technische Universität Dortmund, Dortmund.

18. Erickson, B. H. (1979) Some problems of inference from chain data, *Sociological Methodology*, **10** (1) 276–302.

19. Gabler, S. (1992) Schneeballverfahren und verwandte Stichprobendesigns, *ZUMA-Nachrichten*, **31**, 47–69.

20. Scheiner, J., K. Sicks and C. Holz-Rau (2014) Generationsübergreifende Mobilitätsbiografien-Dokumentation der Datengrundlage: Eine Befragung unter Studierenden, ihren Eltern und Großeltern (Arbeitspapiere des Fachgebiets Verkehrswesen und Verkehrsplanung 29), *TU Dortmund*, **29**.

21. Manzoni, A., J. Vermunt, R. Luijkx and R. Muffels (2010) Memory bias in retrospectively collected employment careers: A model-based approach to correct for measurement error, *Sociological Methodology*, **40** (1) 39–73.

22. Nolan, A. (2010) A dynamic analysis of household car ownership, *Transportation Research Part A: Policy and Practice*, **44** (6) 446–455.

23. Ehreke, I. and K. W. Axhausen (2015) Modellierung von Arbeitsplatzentscheidungen in Mobilitätsbiographien, in C. Holz-Rau and J. Scheiner (eds.) *Räumliche Mobilität und Lebenslauf – Studien zu Mobilitätsbiografien und Mobilitätssozialisation*, 261–276, Springer, Wiesbaden.

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