

Discussion Papers

492

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Measuring and Explaining the Increase
of Travel Distance: A Multilevel Analysis
Using Repeated Cross Sectional Travel Surveys

Berlin, Juni 2005

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1 Introduction

Spatial mobility in the industrialised countries is ever increasing. In West-Germany the total mileage travelled annually by all modes of transportation grew by 40 % over the last two decades (1982 to 2002) to 900 billion kilometres, with the reliance on the use of the car becoming more pronounced. Now 80 % of travel as measured in kilometres is by car drivers and passengers.

Over this period of time, travel as measured by the number of trips undertaken by the population increased less dramatically by 20 % and the modal share of car increased to currently 61 %. There are numerous factors that drove both growth and change, some of them structural, some behavioural:

- The population in West-Germany grew by 10 %.
- At the same time the number of households increased by some 20 % but only in the segment of one or two person households. The average size of households is now down to 2.2 persons.
- Age structure and economic participation of the population changed substantially, especially as the baby boomers – born until the late sixties – are now well into their economic active life while – in parallel to the increasing life expectancy – the appearance of the retired population transformed to a more active and mobile life style.
- Less than one fifth of the households now do not own a car, as the fleet grew by more than 50 % in those 20 years; nearly 30 % of the households hold more than one car.
- The number of people holding a driver's license showed a sizeable increase, in the age-groups up to 50 years nearly every person has a license now with no disparities between genders.
- By now over 80 % of the persons owning a driver's license report that they have a car at their disposal as they wish.
- Increasingly disperse settlement structures characterise the spatial distribution of homes, workplaces and other facilities.

- The latter development was interacting with an expanded supply of transportation infrastructure and services, both in terms of quantity and quality provided.

2 Concept of paper

We want to shed some light on the development of person mobility by analysing the repeated cross-sectional data of the four National Travel Surveys (NTS) that were conducted in Germany since the mid seventies.

The above mentioned driving forces operate on different levels of the system that generates the spatial behaviour we observe: Travel demand is derived from the needs and desires of individuals to participate in spatially separated activities. Individuals organise their lives in an interactive process within the context they live in, using given infrastructure. Essential determinants of their demand are the individual's socio-demographic characteristics, but also the opportunities and constraints defined by the household and the environment are relevant for the behaviour which ultimately can be realised.

In order to fully capture the context which determines individual behaviour, the (nested) hierarchy of persons within households within spatial settings has to be considered. The data we will use for our analysis contains information on these three levels. With the analysis of this micro-data we attempt to improve our understanding of the afore subsumed macro developments. In addition we will investigate the prediction power of a few classic socio-demographic variables for the daily travel distance of individuals in the four NTS data sets (Figure 1), with a focus on the evolution of this predictive power.

The additional task to correctly measure distances travelled by means of the NTS is threatened by the fact that although these surveys measure the same variables, different sampling designs and data collection procedures were used. So the aim of the analysis is also to detect variables whose control corrects for the known measurement error, as a prerequisite to apply appropriate models in order to better understand the development of individual travel behaviour in a multilevel context. This task is complicated by the fact that variables that inform on survey procedures and outcomes are only provided with the data set for 2002 (see Infas and DIW Berlin, 2003).

The paper is organised as follows: we first introduce the NTS data used, then we describe the usefulness of the multilevel approach to model nested data, together with two hitherto performed applications in travel behaviour research. Using multilevel models, we then gradually build up a complex model, which has two purposes: first, it will be able to reproduce the cor-

rect travel distance levels of the cross sectional surveys utilised, by means of controlling for appropriate variables. At the same time, the model is aimed to show new and interesting findings concerning size and development of important covariates once a true comparison of the cross- sections is possible.

We conclude the paper with a brief discussion of the results, and derive some important requirements for future travel behaviour forecast and planning research analysis.

3 The repeated cross-sectional NTS data

National Travel Surveys are large-scale, multi purpose cross-sectional household surveys financed and supervised by some national authority. They measure individual travel behaviour in conjunction with its assumed determinants, i.e. socio-demographic characteristics, regional inventories and available means of transportation. Figure 1 informs on similarities and basic differences in the design of the NTS in (West) Germany that have been collected four times: in 1976, 1982, 1989, and 2002. While having the same core contents, these surveys differ in some aspects of additional content and design elements. The sampling strategies and the sample sizes reflect the need to cover both seasonal and regional variations of travel. Thus all four NTS have substantial sample sizes of about 40.000 (1976, 1982, 1989) or over 60.000 (2002) persons, who reported the relevant aspects of their travel behaviour during one day. Different sampling schemes were employed in the surveys and may have some influence on the results discussed later. In 1976 and 2002 the samples were drawn from official public person registers with stratified random sampling; in 1982 this was done for one third of the sample while two thirds were sampled by address random route and in 1989 random route was the only method used. Of course this different sampling schemes have consequences first of all on the household size distribution and the spatial distribution of the sample. Information on survey methods is only available in the 2002 data, but possible effects play a minor role.¹

Here we use an unweighted subset of these data and restrict our analysis to persons older than 17 years who live in West-Germany, were sampled on a working day and reported at least one trip.²

The four levels of which the data is clustered may be considered in more detail as:

- (1) The *years* of the cross-sectional National Travel Surveys are represented in full in the data as all four surveys covered seasonal and regional variations over the 12-month period.

¹ E.g., we tested the influence of using proxy interview methods (i.e. we have the three categories: only PAPI interview/ proxy interview/ personal interview). An analysis of variance comparing the differences in our sample used result in a non significant difference of the mileage means ($F=0.11$).

² We model workday behaviour only since we know from other analysis that the explanatory structure is very different on weekends and can hardly be captured in one model by weekday dummies, see Kloas and Kunert 1994, Chlond and Lipps 2000.

- (2) As a proxy for land-use, density and infrastructure supply stands the size of the *communities* in which the individuals live; after a suitable aggregation, six categories by number of inhabitants resulted.
- (3) The *household* is the simplest representation of the basic unit of demand in which activities are organised, budgets and goods (e.g. cars) are being shared, similar attitudes are prevalent and the socio-economic status of the members is in general comparable.
- (4) Finally, the *individuals* who perform their roles and tasks within the household form the lowest level in this hierarchy on which the behavioural variable is measured.

Note that one interesting level, namely the short term time horizon is not included in the data. Examples for the analysis of data sets which observe individuals over a longer time span, i.e. analysing the intrapersonal variation of travel behaviour can be found in e.g. Lipps (2001) for the intrapersonal analysis of a one week survey period, or Axhausen et al. (2002) for the intrapersonal analysis of a six week survey period investigated.

4 Multilevel analysis and its application to travel research

The appropriate methodology to analyse hierarchical nested data and to identify context effects is multilevel modelling which has been developed in the social, medical and biological sciences. These models attempt to describe the contextual nature of the data while accounting for the variation in the dependent variable originating from multiple levels (Goulias, 2000). Besides this content related reason for using multilevel techniques there are statistical ones as well. Ignoring the intra-group correlation in the levels (or clusters) may result in biased standard errors and confidence intervals: Although the subject of interest is the single individual, the contexts in which these individuals are nested usually induce systematic differences (Kreft and de Leeuw, 1998). Within clusters a higher homogeneity can be assumed than by simply drawing a random sample, leading to design effects (Gabler and Häder, 2000). As multilevel modelling accounts for the clustered structure of the observations, correct standard errors may be substantially higher than in a regression analysis, whose statistic inference is therefore misleading. Below, we will present two models as an example, one with a correct multilevel specification, the other using standard regression techniques. We will show that not only standard errors of the estimated parameters will be underestimated using regression techniques, but also will some of the absolute levels be biased.

In mobility research the multilevel concept has only recently been adopted and a limited body of literature can be reviewed that falls into two general approaches

- (1) by explicitly considering some hierarchical nature of the data (e.g. individual – household – region) or
- (2) by additionally accounting for repeated measurements from longitudinal surveys with a nested structure on the individual or household level. With the help of a longitudinal survey, the individual variation of behaviour can be analysed.

In a multilevel analysis, as a starting point, the total variance is usually decomposed into the context specific shares, by means of a variance components decomposition (see below). By stepwise including explanatory variables, these variance components are in the following tried to be minimised.

A problem related to research questions like ours, which still has to be solved, is the potential endogeneity of individual behaviour: does the individual show a certain behaviour because it

is living in a specific context (higher level impacts behaviour on lower level), or does the individual look for a suitable context to be able to behave according to its attitudes (lower level “impacts” behaviour on higher level). This question would deserve an in depth analysis, e.g. by using panel data. In addition, confounding effects may be a problem, i.e. when effects on a certain level have impacts on different levels. We will come back to this issue during the discussion of the models to be developed later.

As an example for approach (1) Borgoni et al. (2002) use 1997 Austrian micro-census data to focus on the influences of household characteristics and one regional variable on car ownership and use, the latter measured by annual mileage. They consider two levels, the households with 15 000 units, and the regions with 35 units, which are actual NUTS3³ local areas, not typologies of regions. They evaluate different model formulations and find that household characteristics affect car ownership and use, yet the multilevel analysis reveals regional heterogeneity which cannot be accounted for even if population density is controlled by. Thus they conclude that there exists some regional clustering of specific household types in Austria. Additionally, there may be regional variables whose inclusion might further reduce the regional heterogeneity, but which are not available.

Approach (2) is employed by Goulias (2000). He not only takes the nested hierarchy of person and households but also repeated measurements into account. He studies the dynamics of time allocation to activities in a day over the years of a panel survey. Among his most important findings are the large variance contributions of each level considered and the lack of symmetry in change over time.

³ NUTS = Nomenclature of Units for Territorial Statistics.

5 Starting approach: Variance Components

For the analysis of the development of travel in West-Germany in the course of time, we use the logarithmic transformation of the daily travel distance (\ln_km) of trip-making adult individuals in the four data sets as the dependent variables. The variable \ln_km follows approximately a normal distribution. All analysis use unweighted data.⁴ The most important figures, i.e. log of mileages and the distributions of the variables used in the analysis to follow can be found in Table 1.

For our analyses, we use the *MLwinN* software, which now can be considered as a standard analysis tool for multilevel problems.⁵ The underlying multilevel regression equation with the three levels community, household, and individual, may be written as follows:

$$\ln_km_{comm, hh, ind} = \sum coefficient_i * (fixed) variable_i + \sum coefficient_{j, comm, hh, id} * (random) variable_j$$

with

$$coefficient_{j, comm, hh, id} = c_j + v_{j, comm} + u_{j, comm, hh} + e_{j, comm, hh, ind}$$

The random components $v_{j, comm}$, $u_{j, comm, hh}$ and $e_{j, comm, hh, ind}$ (some of which may be 0) are supposed to follow a normal distribution $N(0, \Omega_{var})$, $var \in \{v, u, e\}$, and the Ω_{var} are estimated on the level on which the variable is defined. If several variables are modelled as random on the same aggregation level (i.e. Ω is a matrix), the non diagonal elements of Ω are the covariances of the respective coefficients.

Because we like to explicitly analyse the mileage development, we do not use “year” as a level specification, but rather define fixed dummy variables for 1976, 1982, 1989, and 2002. The simplest formulation of a multilevel model however, not taking into account any covariate is given by M1 in Table 2.

Here, the only fixed effect is the absolute term that indicates the overall mean for \ln_km . We find that the variation in the dependent variable attributable to the HOUSEHOLD amounts to

⁴ We restrict our analysis to persons who were mobile on their sampled day since it is not documented for the earlier three surveys whether the high proportion of persons with zero trips resulted from immobility or was a form of nonresponse. Thus we do not model the total but the “reported mobile” population. Therefore we perform unweighted analysis to avoid confounded effects of sample selection and weighting in our interpretation. Anyway, a weighted analysis has only very minor effects on the results.

⁵ <http://multilevel.ioe.ac.uk/>

0.467, as compared to the INDIVIDUAL specific variation which is 1.550. Thus the household level accounts for 23 % and the individual level for 77 % of the total variation.

As we know that there is a time trend and that there were structural shifts in the population over the time span covered with our data (household size, age distribution, etc.) we first include the year dummies (model M2 in Table 2). The model improves significantly⁶, and the constant terms now exhibit the secular trend in average daily travel distance, rising significantly from 2,45 in 1976 to 2,91 in 2002, also accounting for β_0 . That in 1989 this term (2,57) deviates from the trend can be explained by systematic measurement errors that have been detected for this survey (Kunert, 1998). One problem is that numerous proxy interviews have been conducted with a person of a household, who gave information about highly mobile household members. An underreporting of trips seems probably with this design. The basic statistics depicted in Table 1 confirm further differences in the distributions: in 1989, too many adults do not own a car, the proportion of small communities is very low, as opposed to that of the communities with 100.000 – 500.000 inhabitants, and there are many one-person households included in the sample. Together with systematic measurement errors resulting from defective proxy interviews, this lead to a too low level mileage.⁷

Interestingly, the HOUSEHOLD level variance decreases by around 8 %, whereas the INDIVIDUAL level variance remains the same. This indicates that given the INDIVIDUAL and HOUSEHOLD effects (in which the INDIVIDUAL effect is nested) as potential variance candidates, the household variance fully captures behavioural and/or methodological differences between the cross-sections considered.

Once the time effect is controlled for, it is possible to include community (size) as a random effect, in which the households are nested.⁸ Apart from the improvement of the model, considering the random effects on the community (size) level, it can be shown (model M3 in Table 2) that more than 20 % of the household related variation is solely due to the different community sizes. Thus different spatial structures exhibit a considerable portion of behavioural differences.

⁶ The difference of the $-2 \cdot \log$ likelihood statistics is chi-square distributed with the additional parameters to be estimated equal to the number of degrees of freedom. The null hypotheses is that the extra parameters have population values of zero.

⁷ Even after socio-demographic weighting, this too low level cannot be corrected.

⁸ Only after controlling for the survey year, it is possible to separate time and spatial effects, given the operationalisation of space here.

6 How will traditional predictors contribute to explain variance components?

In the following we stepwise include explanatory variables as fixed effects into the model. We are limited to variables that are comparable in all four datasets and we confine our analysis to a few basic and important influences.⁹ In order to further control for SPATIAL and HOUSEHOLD related effects and to better grasp the “pure” time effect, we first include community size as a fixed (linear) effect into the model, and achieve a significant improvement (M4). The year dummies stay the same, as do the household and individual related random effects, as expected. However, we find a significant decrease of \ln_km with increasing community size, and a 5 % decrease of the community random effect. The latter indicates that about 5 % of the community variation can be explained by the linearly increasing effect of community size.

As will now be shown we stepwise include household specific variables. Model M5 includes the linear effect of household size (measured as 1, 2, 3, 4+ person households), which again leads to a significant improvement, with a slight reduction of the HOUSEHOLD related random effect. All new coefficients are highly significant. The positive coefficient of household size indicates that the mean INDIVIDUAL mileage level in a household is higher the larger the household is. As we analyse the trip distances of persons older than 17 years, we interpret that as the influence of the additional care taking duties of adult household members in households with children.

More interestingly, also the year effect (especially 1989) and the community size effects as well as the SPATIAL random effect change once the linear effect of household size is controlled for. This shows confounded effects between household and community size: the proportion of smaller households in larger communities is higher. So this pre-selection has effects on both levels considered.

In the next step we include car ownership, measured as number of cars per adult in the household. We also include its square to detect nonlinearities, since we hypothesize that the utility

⁹ Here we want to model the development of travel distance using repeated cross-sectional data, and applying multilevel analysis tools. Surely further influences on travel distances exist and could be incorporated in a more complex model as would be needed for forecasting or policy evaluation. As an example for modelling travel distances in this respect see Axhausen et al. 2004.

of additional cars diminishes with higher motorisation in the society. In order to disentangle linear and nonlinear effects, we start with the number of cars per adult, and arrive at the (again significantly improved) model M6. Concerning the year dummies, the absolute term still increases over time (with the caveat already given for the 1989 data, now having an insignificant year coefficient), although the magnitude is much smaller than in model M5. The reason is that via the more or less monotonously increasing ownership level, the variable car, which is now linearly included in the model and has a large coefficient, captures most of the yearly increase in mileage.

Interestingly, not only the HOUSEHOLD random effect decreases by around 20 %, also the SPATIAL random effect decreases by almost a third. The INDIVIDUAL specific level variation changes only very slightly. Concerning the spatial variance the same interpretation holds than in terms of the decrease of the yearly mileage difference: the inclusion of car ownership is suitable to explain a high portion of the variance between the areas, because in smaller communities, the car per adult rate in a household is higher, and therefore explains the higher mileage level in these areas to a certain extend. This is in addition confirmed by a decrease of the fixed effect of community size. A similar interpretation holds in terms of the effect of the household size.

In model M7, we incorporate the quadratic car per adult coefficient, with an again significant model improvement. Most interestingly the household size fixed effect further decreases, indicating that about 20 % of the effect of household size is included in the *linear* effect of cars (M5 -> M6) and further 20 % are included in the *quadratic* effect (M6 -> M7). The year dummies do not change much; the time effect of cars can thus be captured by the linear term alone. The concave dependency between number of cars per adult and mileage indicates only small mileage increases for those households with an already very high car ownership level. The maximum mileage level is reached with a car ownership level of 1,6 cars per adult.¹⁰

We now consider a model (M8), in which we include an important effect on the INDIVIDUAL¹¹ level: full-time employment, as a simple binary dummy.

¹⁰ Max. of the function $f(x) = 1,59 * x - 0,5$.

¹¹ We found considerable cross-correlations between the individual variables full-time employment, gender and age, respectively. We therefore decided to only consider full-time employment, because this variable shows the most interesting development over time.

The model improves enormously. Expectedly, being full-time employed increases daily mileage considerably. There is a strong interdependency with car possession: the impact of car ownership decreases to a large extent (namely to the level of the not full time employed), with the quadratic term however increasing.

Interestingly, the year coefficient's spread increase once full-time employment is included in the model. This shows the different impact which full time employment has in the different years. The INDIVIDUAL random effect decreases as expected; a part of this reduction is being "transferred" to the HOUSEHOLD random effect, due to supposed confounded effects.

The next model M9 separates the effects of full time employment by year: not surprisingly from Model M8, the yearly development rises much more steeply, with a now for the first time monotonously increasing coefficient. This is expected from the population behaviour.

The stronger increase of the year coefficients in Model M9 compared to model M8 and especially model M7 implies a strong increase of the mileage of the not full time employed persons. In addition, the cross level effects of year and full time employment show a sharply decreasing¹² influence: the 1976 coefficient for the impact of full time employment on mileage is more than twice as high as that in 2002. Taken together, there is a levelling tendency in terms of full time employment in that this variable loses more and more its mileage discriminating power.

We suspected from Model M9 that it might be worth to separate the effect of the number of cars per adult by year. However, although the model improves significantly, only the 1989*car effect is significant, and some of the new coefficients alternate between two instable states when estimating model M10. We therefore only keep the 1989*car effect to arrive at model M11. Compared to model M9, the parameters do not change a lot, however, the year effect size is now as one would expect from the yearly mileage increase in everyday travel in the population as is supported by aggregate statistics by numerous sources (e.g. BMVBW, 2004): only considering the pure time effects, the increase between 1976 and 1982 amounts to $\exp(0,19)$ (21 %), between 1982 and 1989 to $\exp(0,31-0,19)$ (13 %), and finally between 1989 and 2002 to $\exp(0,55-0,31)$ (27 %). Thus controlling for employment and car-ownership can to some extent take account of the presumed underreporting of tripmaking.

¹² The same holds for gender, a variable not explicitly investigated in this article. Although the regression coefficients of these year interaction variables decrease, the significance do not change.

An addendum to model M11 is model M12 (Table 3): here we dropped the constant term, and model the household and individual random effects of the four time dummy variables instead. We also model the random effect of the interaction variables full time employment by year on the HOUSEHOLD level. The intercepts of the year dummies and the slope of the interaction variables full time employment by year have a negative covariance on the HOUSEHOLD level, of the same (and significant) magnitude in all surveys. This means that in all years, households which have a high “base” mileage level (i.e. large intercept), tend to increase their mileage slower with increasing number of full time employed adults. In this way, a hypothetical bundle of regression lines with the number of full time employed persons in the household as regressor would exhibit a “fanning in” pattern. This may indicate a certain saturation for households with an already high mileage level, as these are usually those with many cars available and/or many full time employed adults.

The steady decrease of the INDIVIDUAL random effect of the intercept is probably a structural effect due to the steady decrease of household size with more and more one person households (who exhibit no INDIVIDUAL random effects within the household).

We finally compare the estimated fixed coefficients of the multilevel model M13 with the results of a standard multiple regression approach. The latter underestimates the mileage effects of full time employment, but slightly overestimates them in terms of the influence of household size and car ownership, see Model M13' in Table 3.

7 Discussion

In our final model M12, we find that the total variance of daily travel distance decreases over time, but this stems mainly from the INDIVIDUAL level while the difference in variances from the HOUSEHOLD level is supposed to be caused by survey design effects. In parallel, the intercept gets larger over time, indicating the secular trend of growing distances travelled by the population, once full time employment (INDIVIDUAL level) separately by year, and car ownership (HOUSEHOLD level) aggregated over years is controlled for.

We further find that traditional socio-demographic household and person characteristics diminish in importance to explain mileage of persons on working days. Moreover the standard errors are too small in the regression equation, indicating a too conservative hypotheses testing.

In the light of these findings, the following can be concluded for planning applications: In the widely used tools for estimating travel demand for planning and forecasting the variables used in order to segment the population into “homogenous person groups” or other a priori classifications (especially separated by employment type) loose prediction power over time because persons and households exhibit increasingly diverse life styles. The loss of importance of the trip motives that have traditionally been the focus of forecasting and planning can well be seen in Figure 3: the increase in kilometres per day is mostly driven by pursuing leisure and shopping activities. And the extend of participation in those activities is less easily explained by the socio-demographic attributes of the population.

Additionally, with less than 20 % of households without and nearly 30 % with more than one car, car-availability has lost some of its discriminatory power as a gateway to overcome spatial distances. The negative quadratic impact of the number of cars per adult in a household on the level of mileage, and the negative covariance between full-time employment and mileage (Table 3, model M12) also indicate a saturation, both with respect to additional cars considered as a mere means to satisfy excess demand, and with respect to the most important individual status commonly characterised by a high mileage level. First, newly purchased cars may be considered as means to satisfy *special* demands, as the diversification of the fleet shows. In this way, the conventionally analysed “marginal utility” measured as additional mileage in the household is decreasing. In recent years, the traditionally not very mobile per-

son groups (esp. not full time employed) catch-up to a certain extent. This means the – even during the recent years – total increase in everyday travel is due to these person groups. Taken together it is worth considering to supplement existing modelling approaches with life-style constructs or segmentations of the population based on attitude statements, as Anable (2005), who points out “that attitudes largely cut across personal characteristics. The evidence clearly shows that the same behaviour can take place for different reasons and that the same attitudes can lead to different behaviours” (Anable, 2005, p. 65).

Significance and amount of the variance components taken together indicate some (AREA level weak significance) or strong (HOUSEHOLD level highly significant) context effects on individual daily distance. Thus it is important to consider all conceptual levels which generate significant variation in the mobility indicator under study. This is especially important for the HOUSEHOLD level, whose variance increases over time, relative to the INDIVIDUAL level.

The comparably low impact of the regional context that is one result of this study is in consent with most of the literature that finds regional influence is nearly negligible when HOUSEHOLD and INDIVIDUAL level attributes are present in the analysis (van Wee and Maat, 2001; Cervero and Kockelman, 1996).

8 References

- Anable, J.* (2005): 'Complacent Car Addicts' or 'Aspiring Environmentalists'? Identifying travel behaviour segments using attitude theory. In: *Transport Policy* 12, 65-78.
- Axhausen, K.W., Beige, S., Bernard, M.* (2004): Grundlagenbericht für die Perspektive des Schweizer Personenverkehrs bis 2030, Prognose über Besitz und Nutzungsintensität von Mobilitätswerkzeugen im Personenverkehr, Schlussbericht für das Bundesamt für Raumentwicklung, Eidgenössische Technische Hochschule Zürich, März 2004, <http://www.ivt.ethz.ch/vpl/publications/reports/ab203.pdf>.
- Axhausen, K.W., Zimmermann, A., Schönfelder, S., Rindsfuser, G. Haupt, T.* (2000): Observing the rhythms of daily life: A six-week travel diary. In: *Transportation* (29), 95-124.
- Borgoni, R., Ewert, U.-C., Fürnkranz-Prskawetz, A.* (2002): How important are household demographic characteristics to explain private car use patterns? A multilevel approach to Austrian data. MPIDR WORKING PAPER WP 2002-006, February.
- Bundesministerium für Verkehr, Bau- und Wohnungswesen (ed.)* (2004): *Verkehr in Zahlen 2004*. Compiled by the German Institute for Economic Research, Deutscher Verkehrs-Verlag, Hamburg.
- Cervero, R., Kockelman, K.* (1996): Travel Demand and the Three D's: Density, Diversity, and Design. Working Paper 674, Institute of Urban and Regional Development. University of California at Berkeley, July.
- Chlond, B., Lipps, O.* (2000): Multimodalität im Personenverkehr im intrapersonellen Längsschnitt. In: *Stadt Region Land, Institut für Stadtbauwesen der RWTH Aachen, Band 69*, http://www.isb.rwth-aachen.de/publikationen/171-182_chlond.pdf.
- Engel, U.* (1998): Einführung in die Mehrebenenanalyse: Grundlagen, Auswertungsverfahren und praktische Beispiele. (WV studium; 182).
- Gabler, S., Häder, S.* (2000): Über Design-Effekte. In: P. Ph. Mohler/ P. Lüttinger (Hrsg.): *Querschnitt. Festschrift für Max Kaase*. ZUMA, Mannheim, 73-97.
- Goulias, K. G.* (2000): Repeated measures multilevel analysis of daily time allocation to activities and travel. CITRANS WORKING PAPER, March. <http://citrans.pti.psu.edu/wpPDF%20files/C%20WP%20-%202000-1.pdf>.
- Hank, K.* (2002): Regional Social Contexts and Individual Fertility Decisions: A Multilevel Analysis of First and Second Births in Western Germany. DIW Discussion Papers 270, Berlin, January 2002.
- Infas, DIW Berlin* (2003): *Mobilität in Deutschland - 2002 Kontinuierliche Erhebung zum Verkehrsverhalten*, Projekt im Auftrag des Bundesministeriums für Verkehr, Bau- und Wohnungswesen, Endbericht, Juni 2003, Bonn und Berlin.
- Infas, DIW Berlin* (2004): *Mobilität in Deutschland – Inhaltlicher Ergebnisbericht*. Im Auftrag des Bundesministeriums für Verkehr, Bau- und Wohnungswesen, Bonn und Berlin. For more information see <http://www.mid2002.de>.
- Kloas, J., Kunert, U.* (1994): Über die Schwierigkeit, Verkehrsverhalten zu messen. Die drei KONTIV-Erhebungen im Vergleich. In: *Verkehr und Technik, Heft 3 und 5, 1994*.
- Kloas, J., Kunert, U.* (1994): Die zeitliche Entwicklung der Bedeutung von Personenmerkmalen für das Verkehrsverhalten. In: *Verkehr und Technik, Heft 11 und 12, 1994*.
- Kreft, I., de Leeuw, J.* (1998): *Introducing Multilevel Modeling*. Sage Publications, London.

- Kunert, U.* (1998): Detecting Long-Term Trends in Travel Behaviour: Problems Associated with Repeated National Personal Travel Surveys. In: Juan de Dios Ortuzar, David Hensher and Sergio Jara-Diaz (eds.): *Travel Behaviour Research: Updating the State of Play*. Elsevier, Amsterdam 1998.
- Lipps, O.* (2001): Modellierung der individuellen Verhaltensvariation bei der Verkehrsentstehung. Schriftenreihe des Instituts für Verkehrswesen der Universität Karlsruhe, Heft 58/2001.
- van Wee, B., Maat, K.* (2001): Land Use and Transport: Are Research and Policy on the Right Track? Paper presented at the Nectar Conference No. 6, EUROPEAN STRATEGIES IN THE GLOBALISING MARKETS, Transport Innovations, Competiveness and Sustainability in the Information Age. 16-18 May 2001, Helsinki, Finland.

9 Tables and Figures

Table 1

Basic Statistics of the four NTS KONTIV 1976, 1982, 1989 and MiD 2002 subsamples

	1976		1982		1989		2002	
	abs.	in %	abs.	in %	abs.	in %	abs.	in %
Person level								
Full employment								
No (0)	9301	47,2	7590	53,1	10316	53,7	13867	66,9
Yes (1)	10417	52,8	6717	47,0	8914	46,4	6857	33,1
Car per adult								
No	3917	19,9	1398	9,8	3398	17,7	1523	7,3
Up to 0,33	6187	31,4	2869	20,1	1770	9,2	1162	5,6
Up to 0,50	9144	46,4	6043	42,2	6829	35,5	7680	37,1
Up to 1,00	470	2,4	3992	27,9	7119	37,0	9799	47,4
Up to 1,50	0	0,0	3	0,0	47	0,3	439	2,1
Up to 2,00	0	0,0	2	0,0	67	0,4	93	0,4
Up to 3,00	0	0,0	0	0,0	0	0,0	28	0,1
Community size								
Inhabitants								
Under 2 000	1186	6,0	973	6,8	341	1,8	956	4,6
2 000 to under 5 000	2383	12,1	1171	8,2	1669	8,7	1273	6,1
5 000 to under 20 000	4385	22,2	3390	23,7	4797	24,9	6499	31,4
20 000 to under 100 000	5410	27,4	4178	29,2	5084	26,4	5415	26,1
100 000 to under 500 000	2565	13,0	2445	17,1	3963	20,6	3289	15,9
500 000 plus	3789	19,2	2150	15,0	3376	17,6	3292	15,9
Mean log-km	2,46		2,66		2,59		2,93	
Mean km	31,27		35,63		38,82 ¹		42,70	
Total n persons	19718	100,0	14307	100,0	19230	100,0	20724	100,0
Household level								
Household size								
1	831	8,1	816	11,4	3740	31,8	1596	13,6
2	2520	24,6	2133	29,8	3480	29,6	4593	39,0
3	2568	25,1	1824	25,5	2330	19,8	2227	18,9
4	2565	25,1	1596	22,3	1630	13,9	2352	20,0
5	1139	11,1	641	9,0	490	4,2	730	6,2
6 and more	605	5,9	136	1,9	74	0,6	280	2,4
Community size								
Inhabitants								
Under 2 000	598	5,8	471	6,6	180	1,5	516	4,4
2 000 to under 5 000	1196	11,7	555	7,8	942	8,0	694	5,9
5 000 to under 20 000	2220	21,7	1621	22,7	2759	23,5	3548	30,1
20 000 to under 100 000	2821	27,6	2070	29,0	3037	25,9	3077	26,1
100 000 to under 500 000	1370	13,4	1270	17,8	2507	21,3	1903	16,2
500 000 plus	2023	19,8	1159	16,2	2319	19,7	2040	17,3
Total n households	10228	100,0	7146	100,0	11744	100,0	11778	100,0

continued

Table 1 (continued)

Basic Statistics of the four NTS KONTIV 1976, 1982, 1989 and MiD 2002 subsamples

	1976		1982		1989		2002	
	abs.	in %	abs.	in %	abs.	in %	abs.	in %
Mileage (daily kilometres, transformed to natural logarithm) per individual								
By Household size	1976		1982		1989		2002	
1	2.0		2.5		2.4		2.7	
2	2.3		2.5		2.5		2.8	
3	2.5		2.7		2.7		3.0	
4 and more	2.5		2.7		2.7		3.0	
By Community size (+ inhabitants)								
Under 2 000	2.8		3.0		2.8		3.3	
2 000 to under 5 000	2.6		2.7		2.8		3.2	
5 000 to under 20 000	2.4		2.7		2.6		3.0	
20 000 to under 100 000	2.4		2.6		2.5		2.9	
100 000 to under 500 000	2.4		2.6		2.5		2.8	
500 000 plus	2.5		2.7		2.6		2.8	
¹ The increase of the mean mileage between 1982 and 1989 with decreasing log mileage occurs because of the nonlinear transformation, applied to a different sample distribution. Source: KONTIV 1976, 1982, 1989, MiD 2002, own calculations, unweighted.								

Table 2
Multilevel Models M1 – M11 for ln_{km}

Parameter	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11
beta 0	2,65	2,45	2,45	2,63	2,24	1,90	1,82	1,56	1,44	1,41	1,41
Year dummies											
1976 *											
1982		0,19	0,20	0,20	0,22	0,06	0,04	0,11	0,20	0,23	0,19
1989		0,12	0,13	0,14	0,21	0,00	-0,01	0,07	0,22	0,31	0,31
2002		0,46	0,49	0,48	0,52	0,18	0,18	0,38	0,57	0,52	0,55
Community size				-0,05	-0,03	-0,02	-0,02	-0,02	-0,02	-0,02	-0,02
Household size					0,11	0,09	0,07	0,07	0,07	0,07	0,07
Cars per adult						0,99	1,59	1,29	1,28	1,37	1,36
1982 cars p. adult										-0,08	
1989 cars p. adult										-0,19	-0,20
2002 cars p. adult										0,05	
Cars p. adult squared							-0,50	-0,42	-0,40	-0,42	-0,40
Full employment								0,68			
1976									0,91	0,90	0,90
1982									0,74	0,75	0,74
1989									0,61	0,63	0,63
2002									0,44	0,43	0,43
Random effects											
COMM RE (beta0)			0,094	0,089	0,084	0,062	0,064	0,061	0,064	0,064	0,065
HH RE (beta0)	0,467	0,430	0,349	0,350	0,344	0,288	0,280	0,371	0,374	0,373	0,373
IND RE (beta0)	1,550	1,554	1,552	1,553	1,551	1,534	1,533	1,354	1,342	1,342	1,342
-2loglikelihood	259690	258730	258417	258334	257990	255004	254731	250106	249763	249730	249736
* Reference category											
N = 73 979 individuals											
Grey = not significant on 5 % level.											

Table 3
Multilevel Models M12 and M13 for \ln_km

Parameter	M12 ID, HH RE by years				M13 multilevel specification	M13' standard regression
beta 0						
Year dummies						
1976	1,42				1,43 (0,032)	1,44 (0,028)
1982	1,61				1,62 (0,033)	1,63 (0,030)
1989	1,73				1,74 (0,032)	1,72 (0,028)
2002	1,97				1,98 (0,034)	1,97 (0,029)
Community size	-0,02				-0,019 (0,005)	-0,017 (0,004)
Household size	0,07				0,065 (0,006)	0,072 (0,005)
Cars per adult	1,36				1,353 (0,043)	1,370 (0,040)
1982 cars p. adult						
1989 cars p. adult	-0,20				-0,211 (0,036)	-0,157 (0,035)
2002 cars p. adult						
Cars p. adult squared	-0,40				-0,400 (0,030)	-0,410 (0,027)
Full employment						
1976	0,91				0,902 (0,019)	0,849 (0,019)
1982	0,74				0,736 (0,022)	0,670 (0,022)
1989	0,63				0,630 (0,018)	0,577 (0,020)
2002	0,44				0,437 (0,019)	0,412 (0,020)
Random effects	1976	1982	1989	2002		
HH RE (beta0)	0,73	0,61	0,64	0,56		
IND RE (beta0)	1,41	1,34	1,16	1,19		
CoV (intercept, full)	-0,30	-0,22	-0,30	-0,29		
-2loglikelihood¹	249375				no comparable fit statistics	
N = 73 979 individuals					coefficient (standard error)	
¹ We omit the statistics for model M13, as there is no comparable statistics available for regression analyses.						

Figure 1

Basic sample design elements of the NTS in West-Germany

Same core contents: Basic socio economic variables of individuals and HH, similar mobility indicators

	1976	1982	1989	2002
Sampling	population register	reg and random route	random route	population register
Survey mode	Self Completion Questionnaire (travel diary), by Mail		SCQ, by Interviewer	Mixed CATI + Mail SCQ
Target population	Households speaking German			
Persons eligible	From 10 years		From 6 years	From 0 years
Diary days	2 or 3	1	1	1
Net sample size persons	41.000	39.000	42.000	68.000
Response rates	72 %	66 %	64 %	42 %

Figure 2
Development of car ownership in West-Germany

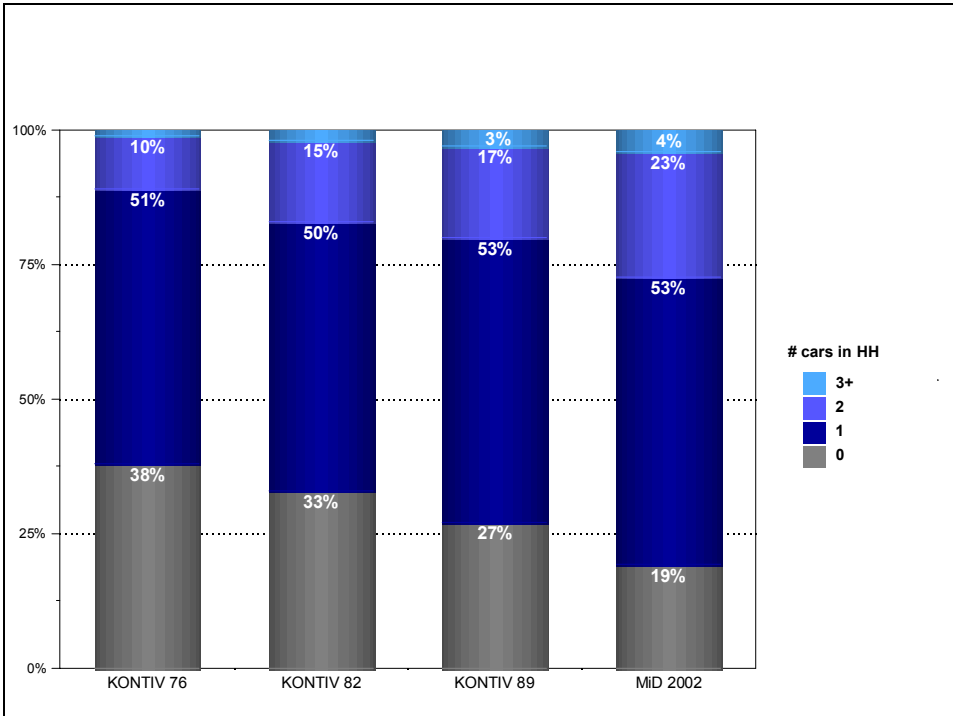


Figure 3
Volume of trips and mileage in West-Germany by purpose, 1982 and 2002

