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Stefan Schönfelder

URBAN RHYTHMS – MODELLING THE RHYTHMS OF INDIVIDUAL TRAVEL BEHAVIOUR

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URBAN RHYTHMS –
MODELLING THE RHYTHMS OF INDIVIDUAL TRAVEL BEHAVIOUR

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PhD thesis
Doktorarbeit

Urban rhythms
Modelling the rhythms of individual travel behaviour

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December 2006

Institut für Verkehrsplanung und Transportsysteme
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Abbreviations

ABA	Activity Based (Analysis) Approach
AFT	Accelerated Failure Time (model)
AKTA	Afgifter i Københavns Trafik (Alternative Driving and Congestion Charging)
AML	Arc Macro Language
CATI	Computer-Assisted Telephone Interview
ETH	Eidgenössische Technische Hochschule (Zürich) (Swiss Federal Institute of Technology)
GIS	Geographic Information System
GPS	Global Positioning System
ISA	Intelligent Speed Adaptation
IVT	Institut für Verkehrsplanung und Transportsysteme (Institute for Transport Planning and Systems), ETH Zürich
OLS	Ordinary Least Square (Regression)
PAPI	Paper-Assisted Pencil Interview
SPN	Shortest Path Network
SVI	Vereinigung Schweizer Verkehrsingenieure (Swiss Association of Transportation Engineers)

PhD thesis

Urban rhythms
Modelling the rhythms of individual travel behaviour

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Abstract

The recent availability of longitudinal data on individual trip making and activity behaviour has enabled analysts to get new insights into the structures and motives of daily life travel. Travel diary data sets such as Mobi*drive* (six-week continuous travel diary survey) and GPS observations such as Atlanta (up to 2 years of vehicle instrumented GPS monitoring) are exciting sources of information for the description and modelling of the variability of individual travel patterns. The investigation of long-term temporal and spatial phenomena of travel demand is adding to the analysis repertoire of Activity Based Analysis (ABA) which identifies this area as an important issue for research and practice.

This thesis picks up two aspects from the wide field of the intra-personal investigation of travel behaviour which are the periodicity in activity demand and the long-term structures of destination choice and activity spaces. These two issues stress the regularity and the stability of day-to-day travel behaviour which has been often neglected in travel behaviour analysis in favour of the legitimate intention to search for complexity and variability in the first place.

The first stream of analysis concentrates on the description of the temporal patterns of activity demand by Survival Analysis techniques such as hazard models. The approach which considers parametric as well as non-parametric models is chosen to capture the specific characteristics of interval duration data. The models reveal the effects of socio-economic attributes of travellers on the periodicity of activity execution.

The focus of the second stream of analysis is the description and measurement of the spatial distribution of activities. Activity locations which are frequently visited over prolonged periods are structural elements of the activity spaces which may be understood as a “manifestation of our everyday lives”.

The thesis develops several measurement approaches which focus on the enumeration and mapping of unique locations and the transformation of point patterns into continuous representations of locational choice. The identification and measurement of revealed individual activity spaces is believed to increase transport planning's ability to realistically define choice set for destination choice.

The analysis is based on a range of individual panel data sets of different data collection methods and survey areas which provides a great variety of behavioural patterns and regional peculiarities. These data sets span the range from rural village and small town (Canton Thurgau, Switzerland) to metropolitan environments (Copenhagen or Atlanta). The analysis tries to trace the possible impacts of these scale differences.

The thesis offers interesting new findings on the motives of recurrent patterns of travel and especially on the longitudinal structures of people's destination choice. A multifaceted and ambiguous character of daily life travel is revealed. Whereas sound routines in time and space seem to dominate daily life, individuals show a considerable amount of variability, flexibility and variety seeking in travel and activity behaviour.

The results have strong implications for further methodological developments in travel behaviour analysis and for the ongoing practitioners' discussion of how to influence people's mobility patterns.

Keywords

Travel behaviour; rhythmic patterns; routines; variety seeking; longitudinal travel data; destination choice; hazard models; activity space; IVT; ETH

Preferred citation style

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Doktorarbeit

Urban rhythms
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Kurzfassung

Die Verfügbarkeit von aktuellen Langfristdaten zur individuellen Mobilität ermöglicht der Verkehrsforschung, die Strukturen und Motive der Alltagsmobilität genauer zu analysieren. Datensätze aus Mobilitätserhebungen wie Mobi*drive* (6-Wochen-Haushaltsbefragung) oder Atlanta (Fahrzeugmonitoring durch GPS über bis zu zwei Jahre) sind spannende Informationsquellen für die Beschreibung und Modellierung der Variabilität individueller Wege- und Aktivitätenmuster. Die Analyse der Strukturen des langfristigen Raum-Zeit-Verhaltens ergänzt das Untersuchungsrepertoire der aktivitätenbasierten Verkehrsforschung (*activity based analysis*), die dieses Feld als wichtigen Schwerpunkt für Wissenschaft und Praxis identifiziert hat.

Diese Doktorarbeit widmet sich zwei Aspekten der Alltagsmobilität, nämlich der Periodizität in der Aktivitätennachfrage und den Langfriststrukturen der Zielwahl und der Aktivitätenräume. Die beiden Schwerpunkte betonen in erster Linie die Regelmässigkeit und die Stabilität des Verkehrsverhaltens – Phänomene, die bisher oft zugunsten der (legitimen) Suche nach der Komplexität und der Variabilität im Verhalten unberücksichtigt blieben.

Der erste Teil der Untersuchungen konzentriert sich auf die Beschreibung der zeitlichen Muster der Aktivitätennachfrage. Dabei werden Techniken der Survival Analysis, insbesondere Hazardmodelle verwendet. Der Ansatz berücksichtigt nicht-parametrische sowie parametrische Modelle und zielt im Detail auf die Analyse der Intervalldauern zwischen zwei gleichartigen Aktivitäten. Die Modelle erlauben es, die Effekte von sozio-ökonomischen Attributen der Reisenden auf die Regelmässigkeit der Aktivitätenausübung zu testen.

Die zweite Analyserichtung ist die Beschreibung und Messung der räumlichen Verteilung von Aktivitätenstandorten. Orte, die über längere Zeiträume regelmässig besucht werden, gelten als strukturelle Elemente des „Aktivitätenraums“, der in der Geographie und Soziologie als “Manifestierung unseres Alltagslebens” beschrieben wird.

Die Dissertation entwickelt dazu verschiedene Masszahlen der Struktur und der Grösse des Aktivitätenraums. Dies sind Ansätze zur Auflistung und Auszählung der beobachteten Standorte und zur Transformation von Standortmustern in kontinuierliche räumliche Darstellungen.

Beide Analysestränge basieren auf einer Reihe von Paneldatensätzen zur individuellen Mobilität, die sich in der Erhebungsmethodik und im räumlichen Bezugsrahmen unterscheiden. Die Datensätze spannen den Rahmen vom ländlichen Raum (Kanton Thurgau) bis hin zu grossstädtischen Gebieten wie Kopenhagen oder Atlanta. Die Untersuchung versucht unter anderem, die potentiellen Einflüsse dieser regionalen Unterschiede aufzudecken.

Als Ergebnis bietet die Untersuchung interessante Ergebnisse zum Charakter und zu den Motiven wiederkehrender Muster der Mobilität und insbesondere zu den Strukturen der Zielwahl. Insgesamt ergibt sich ein vielfältiger und vieldeutiger Charakter der Alltagsmobilität. Während Routinen im zeiträumlichen Verhalten den Alltagsverkehr zu dominieren scheinen, zeigen Verkehrsteilnehmer trotzdem ein deutliches Mass an Verhaltensvariabilität und –flexibilität. Als wichtige Determinante der Zielwahl wird die Suche nach Abwechslung identifiziert.

Die Resultate sind grundlegende Informationen für weitere methodische Entwicklungen der Verkehrsmodellierung, wie beispielsweise für eine realistischere Formulierung von *choice sets* bei der Zielwahl. Zudem ergeben sich Argumente für die verkehrspolitische Diskussion darüber, wie Mobilitätsmuster erfolgreich beeinflusst und gesteuert werden können.

Schlagworte

Verkehrsverhalten; Rhythmische Muster; Routinen; Abwechslungssuche; Langfristbeobachtungen; Hazardmodelle; Zielwahl; Aktivitätenräume; IVT; ETH

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1 The temporal and spatial complexity of daily travel – an introduction

The day-to-day travel behaviour of an individual expresses itself in a variety of activity repertoires and derived movements in time and space. The investigation of those structures over time has long been restricted for several reasons, not the least by the absence of suitable panel data covering prolonged periods of travel behaviour and methods to treat such data. Besides, transport planning has focused on the analysis and the comparison of aggregate or group averages (*inter-personal* differences) whereas the single traveller perspective has not been in the centre of interest. Planners' traditional focus has been predominantly on the provision of capacities rather than on the individual decision making in time and space or the response of travellers towards their surrounding environment.

Research and practice apparently have recognised the need to better understand the details of mobility patterns of persons and households over time. Realising the longitudinal structures of individual mobility allows to design and adjust more efficient measures to influence travel behaviour according to the current transport policy priorities (Long, 1997; Miller, 1999). Since demand management, information and counselling play a more important role for transport policy, generally the traveller as an individual decision maker and his/her travel habits receives more attention in the relevant strategies.

However, the sensitivity of travel behaviour towards supply change (*pull strategies*) as well as demand oriented measures (*push strategies*) has so far mainly been tested by collecting and analysing data based on cross-sectional surveys. Given the traditional aim of obtaining static equilibrium descriptions of flows on transport networks, short duration, as a rule one-day, diaries have been judged appropriate in the past. The higher cost per household recruited for a longer period and the risk of loosing data precision by fatigue or non-response effects were the main impediments to a change of practice[1].

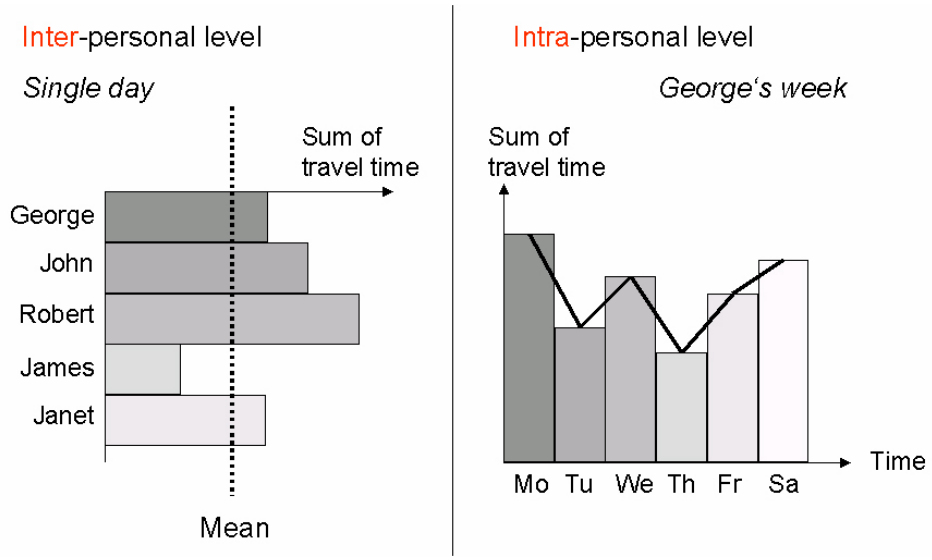
As a consequence, mobility patterns observed on single days have often been interpreted as optimal decisions of the traveller in a state of individual equilibrium. Travel behaviour research has consistently questioned this working hypothesis (see e.g. Huff and Hanson, 1986;

[1] It should be noted though, that per trip one-day diaries are substantially more expensive.

Jones and Clarke, 1988), as daily mobility is subject to a significant amount of variability and flexibility.

Those temporal aspects of individual travel behaviour which may be summarised as *intra-personal variability* (Figure 1) have been the foci of analysis in the *Activity-Based (Analysis) Approach* (ABA) since its emergence thirty years ago (see Kitamura, 1988; Mahmassani, 1988; Pas and Harvey, 1997; McNally, 2000 and Chapter 3 for an introduction). ABA argues that a deeper insight into the temporal structures of mobility is believed to further, for example, the development of advanced disaggregated transport models (Jones, 1981).

Figure 1 Inter-personal versus intra-personal variability



After Pas (1987)

Still, the lack of suitable (individual consecutive panel) data for persons and households has existed – with few exceptions[2] – till the end of the 1990s when the Mobi*drive* 6-week travel diary survey was designed and implemented (Axhausen, Zimmermann, Rindsfüser, Schönfelder and Haupt, 2002). The survey data with great comprehensiveness and exactness offers a range of opportunities for intra-personal analyses and has even increased researchers' interest

[2] One of the few earlier examples of multi-day travel surveys is described in Chapter 3.

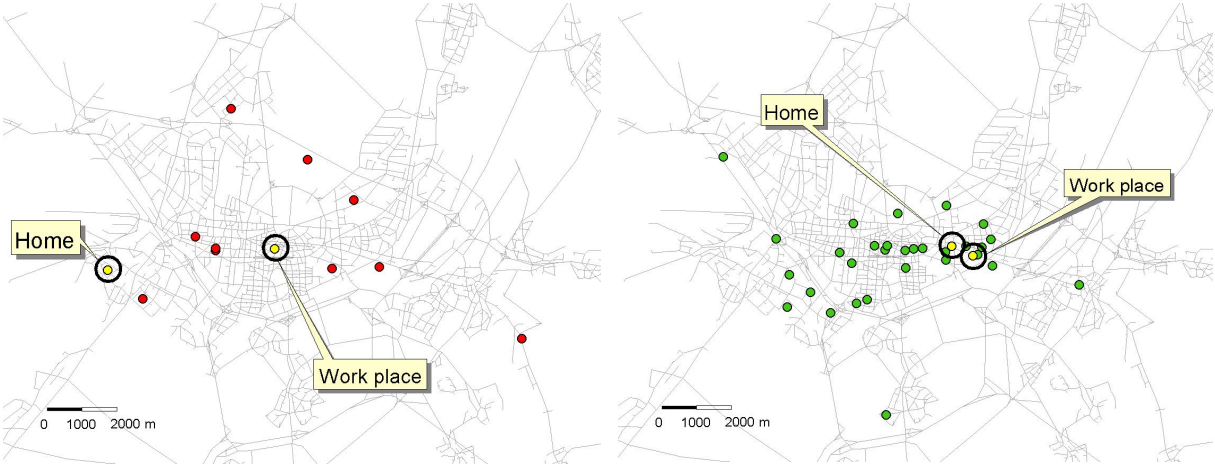
in accessing long-term travel data bases which eventually capture even longer observation periods in activity and trip demand.

This thesis picks up two aspects from the wide field of the intra-personal investigation of travel behaviour which are the *periodicity in activity demand* and the *long-term structures of destination choice and activity spaces*. In general, these two aspects will stress the regularity and the stability of day-to-day travel behaviour which has been – even in the ABA – often neglected in favour of the legitimate intention to search for complexity and variability in the first place (Mahmassani, 1988).

The first stream of investigation, i.e. the analysis and modelling of the *periodicity of activity demand* aims to reveal the structures and the background of recurring temporal patterns in travel behaviour. The analysis covers the identification of recurring patterns, the development of an analytical framework and the exploration of important determinants of the rhythms of daily life. The results are believed to be an important prerequisite for transport policy – in particular traffic control and transport supply strategies.

The second analysis stream which is adding to the spatial aspect of the longitudinal data exploration is the conceptualisation, visualisation and measuring of human activity spaces such as shown in Figure 2. Although there has been substantial theoretical work on locational choice and spatial navigation over the last decades (see e.g. Golledge and Stimson, 1997), there is still need to gain more empirical evidence about the long-term structures of spatial mobility. The identification of revealed individual activity spaces will increase transport planning's ability to realistically define choice set for destination choice (Figure 2 shows an example). In general, this work is aimed to understand better the behavioural mechanisms behind the dispersion and clustering of activities.

Figure 2 Distribution of activity locations in a longitudinal survey (Mobi*drive* data)



Left: Man, 50, fulltime working, 1 child, 120 trips / 6 weeks
Right: Woman, 24, fulltime working, single, 216 trips / 6 weeks

Both aspects of the thesis are analysed using the above mentioned Mobi*drive* observations and further innovative longitudinal data sets which have been made available over the last few years. Given the substantial differences in survey design, sampling and areas, the thesis will offer an interesting synopsis of travel behaviour for different socio-economic and local settings worldwide.

In brief, the thesis provides both, a development of approaches to capture the structures of regularity of behaviour in time and space as well as valuable results for planning and policy. The current worldwide discussion about the introduction of transport pricing, for example, nicely illustrates the need to focus on the latter issue. The question of how rhythms affect response to pricing measures – which is discussed analytically briefly in Chapter 7 – will be among others one of the key success factors of such policy scenario. On the one hand, the acceptability of roadpricing – by travellers and decision makers in policy and planning – is often tempered by concerns over new charges being places on regular, habitual and necessary journeys as well as on missing alternatives to driving. On the other hand, cross-sectional data and their investigation easily fail to answer important analytical questions such as “How many car owners would not be affected by the introduction of a road pricing scheme at all, if charges were imposed only on Monday through Friday?” (see example discussed in Jones and Clarke, 1988).

Claiming a combination of methodological progress and practical value, this thesis is guided by the following two overall research questions:

- Given an analytical shortcoming in the field of long-term travel behaviour of single persons and households, which are the suitable methodological tools to represent these structures and the driving forces behind activity demand and trip making?
- What do the analysis results tell us about the travellers' motives and demand structures and how does planning need to interpret the findings to improve its forecasting tools as well as their transport strategies?

2 Framework and structure of the thesis

The framework of the thesis is given by a linkage of the two complementary analysis streams, i.e. the periodicity in activity demand and the regularities in destination choice behaviour. The different chapters try to answer the following questions:

- Which is the research background of this work? What do we already know about persons' and households daily life structures?
- Which further knowledge would help us to understand and predict longitudinal structures travel behaviour better? What are our assumptions about people's long-term activity demand and the set of places people know and visit?
- Which data bases are appropriate to analyse the regularity in activity demand and locational choice?
- How do concepts of long-term behaviour look like and which are the appropriate methodological tools to capture behavioural routines, rhythms and stability?
- If searching for the determinants of activity demand and spatial usage, which socio-economic characteristics of the individuals need to be considered?
- What are the methodological implications of a deeper understanding of long-term travel behaviour?
- And finally: What is the planning and policy relevance of the expected results?

In more detail, the work is structured as follows: After a brief introduction of the relevance of the subject and the purpose of the thesis (1) and this structural overview (2), the next chapter provides the state of the research as a background of this work: Chapter 3 provides an outline of the paradigm of the Activity Based Analysis (ABA) which is an important methodological precondition of the thesis. In addition, the chapter refers to issues closely linked to the analysis streams. Based on a literature review of relevant conceptual as well as empirical studies, it gives a summary on the

- different temporal phenomena of travel behaviour and their determinants,
- earlier results on the variability and stability of daily life,
- theories of destination choice and activity spaces and
- existing concepts to describe and measure human movements.

The background chapter is followed by the questions (hypotheses) (Chapter 4) which are developed as an outcome of the preceding discussion. The research questions will stress the am-

biguity of daily travel with its strong regularity and periodicity on the one hand and a permanent aspiration of travellers to escape from this habitual monotony on the other hand. The analysis of the temporal as well as spatial behaviour will test this working hypothesis.

Chapter 5 gives a synopsis of the data bases used to reveal the structures of daily mobility. It will provide a detailed description of the different data sources but will also clarify the differences between the observation approaches – especially between travel diary surveys and in-vehicle GPS tracking. The chapter will also provide an overview of the utilisation of the different data sets for the different analyses. A further emphasis will be the crucial post-processing for the GPS traces which generally lack some important behavioural information.

Chapter 6 focuses on the investigation of the periodicity in long-term travel behaviour. It captures the development of a conceptual background for an investigation of the rhythms of activity demand, the presentation of suitable tools and modelling approaches to capture the regularity in daily life and the analysis of the phenomenon *periodicity* itself.

In parallel to the preceding chapter, Chapters 7 and 8 give the development of approaches to visualise and measure human activity spaces as well as a broad (comparative) analysis. Due to the comprehensiveness of the proposed techniques, i.e. the enumeration of trips and locations over time as well as the continuous representation and measurement of space usage, the second stream of analysis is presented in two separate chapters. The end of Chapter 8 provides a synopsis of results by combining the two approaches in a unifying analysis.

The results are discussed in two concluding chapters from a methodological (Chapter 9) and planning/policy perspective (Chapter 10).

3 Theoretical and empirical background

As mentioned above, the investigation of temporal aspects of individual travel behaviour such as the regularity in activity demand was touched in various studies – however, the behavioural periodicity and particularly the longitudinal structures in destination choice have not yet been analysed in detail. This chapter provides the theoretical and empirical background for the following analysis with a focus on the introduction of the research tradition this work is embedded in and the relevant terminology as well as concepts and the most important findings of earlier research. After a compact presentation of the ABA, the remainder of the chapter tries to present the necessary background knowledge for both analytical streams of this thesis.

3.1 Activity based (travel) analysis (ABA)

Since the 1970s the spatio-temporal patterns of activities and trips made by individual travellers and households are the dominant focus of the research into mobility (Jones, 1981; Beckmann, 1983). The theoretical and methodological developments of the *Activity-Based (Analysis) Approach* (ABA) are the scientific outcome of this particular interest. The conceptional foundation of ABA is the finding that the decision to change one's location – and therefore making a trip – is a consequence of a need/demand which cannot be satisfied at the present place. These needs commonly have a physiological, cultural or social character and express themselves in a range of *activities* which are performed at different times and different places. The execution of activities *in time and space* therefore plays the key role in the investigation of mobility structures. This paradigm change within travel analysis and modelling has the consequence that complex behavioural patterns such as periodicity, variability or other temporal phenomena were identified as central objectives of the investigation (see e.g. Kitamura, 1988; Mahmassani, 1988; Jones, Koppelman and Orfeuil, 1990; Pas and Harvey, 1997).

The methodology of the activity based analysis differs fundamentally from the forecasting and planning approaches which were predominant till the 1970s. The traditional models (see Oi and Shuldiner, 1962; Hutchinson, 1974) consider the trip per se as the only predictor for traffic volumes (*trip based analysis*) and neglect the underlying activity demand as well as the individual and environmental circumstances of the trip making. The foremost purpose of these

(four-steps) forecasting models[3] – mainly developed beginning of the 1950s and still widely in use in transport planning – is the analysis of traffic flows based on a highly aggregated data base (see Ortuzar and Willumsen, 1994). This has enabled tools to quickly conceptualise and assess large infrastructure projects like motorways. Activity based analysis and activity based forecasting models in contrast aim to integrate personal mobility and the relationship between human activity patterns, needs and interactions and to forecast individual travel demand based on this complex system (Kutter 1972; Heidemann, 1981; Hanson and Burnett, 1981; Jones, 1981; Pas 1990; McNally, 2000).

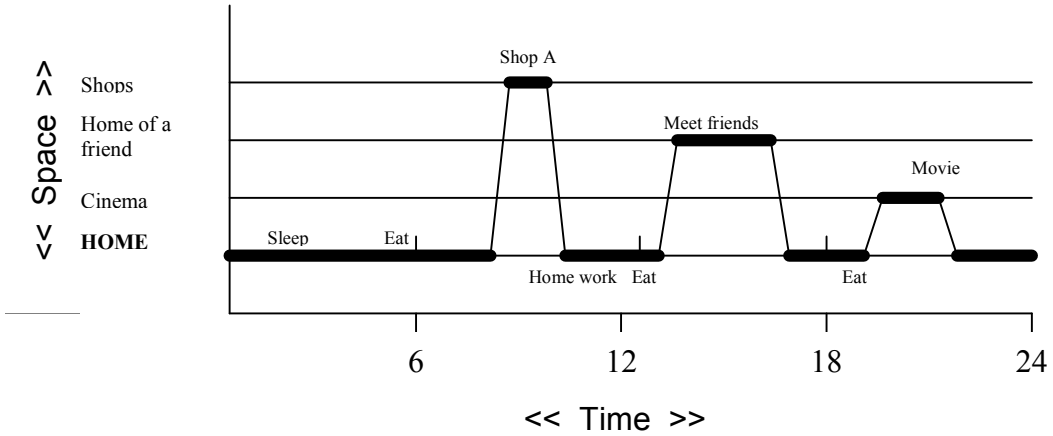
This dissertation refers with its analysis of recurrent travel patterns and the structures of destination choice to this framework of understanding human activities. As this an important prerequisite for this work, a characterisation of the research direction is given in the following (see also Jones, Dix, Clarke and Heggie, 1983):

- Travel may be understood as an induced demand for (out-of-home) activities. Only in few circumstances travel is itself a primary activity (see e.g. Mokhtarian and Salomon, 2001).
- The approach (most often) considers the embedding of trips and activities in sequences. Travel is defined as a transition within a continuous pattern of daily behaviour / of a daily programme which is a sequence of activities in time and space (Figure 3).
- Temporal, spatial as well as interpersonal restrictions are considered explicitly in the analysis and model development. The activity based approach refers to fundamental concepts of time use analysis (see Bhat and Koppelman, 1999) and *space-time geography* (Hägerstrand, 1970 and others).
- Personal travel decisions need to be seen against the traveller's household context. Role models and interactions between the household members are important explanatory elements for the activity based analysis.
- The focus on the analysis of activity execution needs to be combined with a detailed classification of travellers by similar activity demand if complex travel behaviour shall be described, analysed and predicted. The classification by life cycle or lifestyle which often represents similar activity behaviour is a common approach to discriminate travellers in many studies.
- Time is a key concept in the activity based approach. Activity based analysis goes beyond the simple consideration of time as optimisation objective or speed element. On the one hand, timing and duration of activities are important explanatory determinants of complex behaviour, on the other hand, they are themselves of

[3] Trip based forecasting models with the four steps 1) trip generation, 2) trip distribution, 3) mode choice and 4) trip assignment

great interest if analysing dynamics, variability or periodicity within mobility patterns.

Figure 3 Activity and travel from the activity based analysis standpoint



Adopted from Jones et al. (1983) 37

Selected conceptual requirements of activity based analysis

Activity based approaches have particular requirements for the design and contents of travel surveys. If individual travel behaviour shall be described and explained in its full complexity, it is necessary to collect information on the activity system and travel routines of travellers over prolonged periods (see Jones, 1985). Often only longitudinal data may fulfil these requirements.

The explanatory power of analyses with a focus on temporal aspects as well as on durations of processes is dependent on the quality of long-term data (Hanson and Huff, 1982). Two essential points need to be mentioned:

- *continuous observation/reporting* of people's and households' travel behaviour over prolonged periods: The length of the survey period should allow to capture the interrelationship of human behaviour with the recurrent structures of the dynamic surrounding environment.
- a possibly *great degree of exactness and comprehensiveness* in the collection of the daily activity programmes and the relevant static descriptors of travellers and their households. The latter needs to capture socio-economic and structural char-

acteristics of the survey respondents, mobility tool access and – if possible – data on the travellers' attitudes towards their own mobility and transport in general.

In addition to that, the analysis of activity based information is a challenge for the development of suitable measurement approaches for complex travel behaviour (see Chapters 6 to 8). All existing modelling approaches need to be complemented by the described conceptual and methodological foundations which has implications for e.g. the incorporation of structural variables such as car availability, pre-commitments or inner-household relationships as explanatory determinants (Jones *et al.*, 1990, pp. 39).

3.2 Temporal phenomena of travel behaviour and their determinants

The complexity of daily travel patterns is subject to several temporal patterns determined by a set of individual characteristics of the traveller (Hanson and Burnett, 1981). In general, the complexity is an outcome of both, habitual behaviour or routines and variability which may be described as random as well as systematic deviations from the behavioural regularity. The activity based approach has focused on many of those aspects and the factors affecting the behavioural patterns for three decades (see Jones and Clarke, 1988). The different foci of the studies are manifold (Table 1 provides a selective list of relevant publications) and the terminology used to describe the temporal phenomena of travel behaviour often intersects. The overview shows that a wide range of expressions are used synonymously. However, identical terms are chosen for different aspects. This is especially true for the term *variability*: Whereas several studies deal with behavioural variability in the context of inter-personal differences for mobility determinants such as daily travel distances or number of trips, others use variability as a description of changing behaviour of one individual over time. In general, the term *variability* is often used as generic term for the set of phenomena described below.

Table 1 Selected studies on temporal aspects in travel of persons and households

Issue	Examples
Stability	Herz, 1983; Mannering, Murakami and Kim, 1994; Schlich, König and Axhausen, 2000; Schwanen and Dijst, 2003
Variability (intra-personal, inter-personal, systematic)	Pas 1986, 1987; Pas and Koppelman 1986; Pas and Sundar, 1995; Hanson and Huff 1982; 1988a; 1988b; Huff and Hanson, 1986; Abdel-Aty, Kitamura and Jovanis, 1995; Muthyalagari, Parashar and Pendyala, 2001; Guensler, Ogle and Li, 2006
Flexibility	Herz, 1983; Mannering, 1989; Emmerink and van Beek, 1997; Saleh and Farrell, 2005
Rhythmic patterns	Shapcott and Steadman, 1978; Bhat, Frusti, Zhao, Schönfelder and Axhausen, 2004; Bhat, Srinivasan and Axhausen, 2005
Repetitive behaviour	Huff and Hanson, 1986; 1990; Garvill, Marell and Nordlund, 2003; Schlich, 2004
Regularity	Kitamura and van der Hoorn, 1987; Jones and Clarke, 1988; Harvey, Taylor, Ellis and Aas, 1997
Dynamics (especially departure time choice and trip chaining)	Chang and Mahmassani, 1989; Mahmassani, 1997; Mahmassani, Hatcher and Caplice, 1997; Mannering and Hamed, 1990; Bhat, 1998; Goulias, 1999; Mahmassani and Liu, 1999; Steed and Bhat, 2000; Bhat and Steed, 2002; Pendyala and Bhat, 2004
Variety seeking	Borgers, Heijden and Timmermans, 1989; Timmermans, 1990; Kemperman, Borgers, Oppewal, and Timmermans, 2000; Kempermann, Borgers and Timmermans, 2002, Zängler and Karg, 2004; Arentze and Timmermans, 2005

At this point, some definitions of the most important phenomena are given in parallel to what has been found out earlier on their structures and determinants. The definition adds to what has above been presented on the conceptual and methodological context of activity-based analysis.

Habits and routines in (travel) behaviour

Habitual or routinised travel behaviour is the re-use of behavioural segments, sequences or – more general –*solutions* in identical or similar decision situations. An approved behavioural pattern with known costs which has satisfied similar needs in the past is re-used or re-applied. The motive behind the re-application of known alternatives is to avoid costs for the potentially new or additional acquisition of information which might be necessary for the new decision. In the particular context of travel, this becomes obvious for the minimisation or even avoidance of information acquisition to get efficiently from A to B (Goodwin, Kitamura and Meurs, 1990).

Equilibrium of behaviour

Behavioural equilibrium is achieved if all details which determine travel behaviour have remained constant over a sufficiently long period of time and the behaviour has been adjusted to the environmental factors completely (Goodwin, Kitamura and Meurs, 1990). Such an environmental factor is for example the household composition which widely structures daily activity patterns and the induced travel demand. Behavioural equilibrium is a long-term phenomenon which has to be distinguished from random or unexpected short-term adjustments of behaviour which do not have a systematic character.

An interesting question is if there is only one behavioural equilibrium given a single set of factors. It is certainly possible that states of equilibrium differ even if particular situations and events have been experienced in a similar way in the past.

It should be noted here that complete behavioural equilibrium over time is hardly ever observable. Most of the environmental factors are themselves subject of permanent change (seasonal rhythms, current political developments etc.). Even substantially stable determinants of travel such as household related details such as home location, lifecycle and occupation status cannot be defined as entirely constant. They change over longer periods with notable implications for the individual mobility. Behavioural equilibrium therefore remains a theoretical construct – at least from a long-term perspective.

Dynamics

Dynamics of behaviour describes the systematic adaptation of decisions to changing circumstances and to the situative context of travel (i.e. mode, departure, destination, route choice)

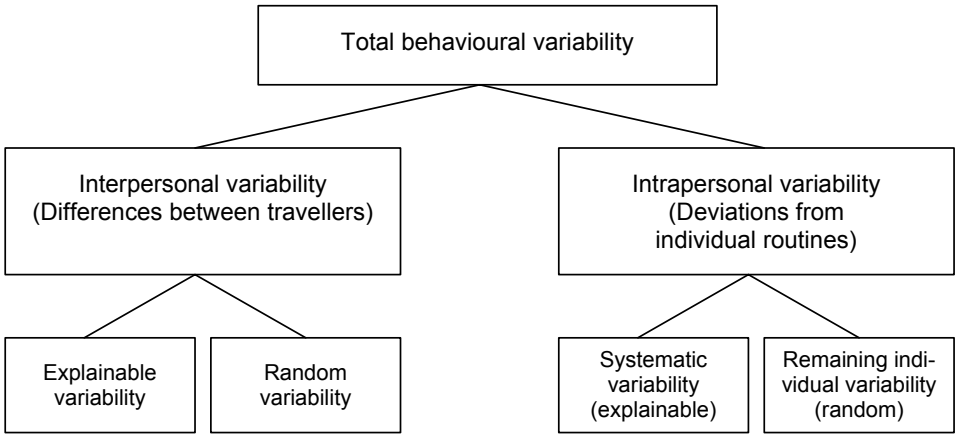
(Kitamura, 1988). Those involve for example short-term reactions of travellers to traffic conditions (e.g. congestion, bad weather) or long-term and structural fine tuning of behaviour towards behaviour influencing variables such working hours, household composition or the change of workplace. Although some of the structural characteristics in the travellers' life occur in periodic intervals (e.g. change of work place), the term rhythm is here only used to describe the periodicity of behaviour at the daily, weekly or monthly level. The development of rhythms of travel behaviour is a reaction of the traveller towards the dynamic and social environment or in other words, fundamental socio-economic alterations in life foster the development of habitual behaviour and rhythms.

Variability: Inter-personal versus intra-personal variability

As briefly mentioned above, the phenomenon of behavioural variability can be discussed from two perspectives: First, the behaviour of two persons almost always differs due to differences in their socio-economic background or attitudes. This aspect of variability is often defined as *inter-personal variability* (Pas, 1987) and may be described as the deviation of the individual behaviour from the mean behaviour of the respective sample or of the socio-economic group the traveller belongs to. In contrast to that, the behaviour of an individual or a household varies considerably if they are observed over periods of time which exceed a pre-defined timespan such as one day (= *intra-personal variability*). Here, variability is a definition for the deviation of behaviour from the usual individual routines and habits which were developed over longer time periods.

Both categories of variability usually have a systematic component - which is explainable or predictable by e.g. personal characteristics - and a remaining random component (Figure 4). Predictable as well as random elements of variability are inherent in models of human behaviour and have implications for the reliability or explanatory power of the models.

Figure 4 Variability in travel behaviour: Components



Adopted from Pas (1987) 432

The variability within persons' or households' behaviour expresses travellers' needs and aspirations which are not constant from day to day and that unforeseen events and circumstances make short-term adaptations of behaviour necessary (Pas and Sundar, 1995). In the context of activity-based approach, intra-personal variability of travel behaviour is given if behaviour deviates generally from routinised activity sequences or from activity / trip attributes such as mode of travel, departure time or size of company.

In the context of this thesis, the intra-personal variability is an underlying theme as recurrent behavioural elements as well as the stability of spatial choice are to be analysed. However, in order to reveal for example the extent of periodicity in daily activity behaviour and to take advantage of the used samples as whole, inter-personal comparisons are systematically made.

Rhythmic patterns[4]

Rhythmic patterns of travel are elements of behaviour which may be observed periodically over prolonged periods of time such as weeks or over the course of a year. These may be complete daily patterns with identical attributes, activity sequences or single main activities or trips. The rhythmic patterns occur on a predictable basis and may therefore be explained "historically", i.e. they are determined by fixed external timetables, circumstances or events

[4] More on rhythmic patterns may be found in Chapter 6.

(Shapcott and Steadman, 1978). Rhythmic patterns are fundamental consequences of habitual behaviour.

Variety seeking

Variety seeking stresses the context and in particular the motivation behind varied behaviour. The phenomenon has been extensively explored in psychology and consumer choice analysis for decades, however, geography and transportation research still face problems to incorporate variety seeking aspects in their models of choice. A good (early) overview about variety seeking in consumer choice analysis is provided by McAlister and Pessemier (1982) whereas for example Timmermans (1990) tries to relate the fundamental conceptual concepts to spatial choice behaviour.

In general, variety seeking stems from two streams of motives which may be summarised as derived and direct motivations (McAlister and Pessemier, 1982) (see also Table 2): First, variety seeking may be described as *derived* as it is often initiated by external factors. Derived variety seeking behaviour is therefore not originally implied by taste variations of the individual decision maker but by changes in the choice situation. Such surrounding factors may be the altered set of choice alternatives or individually perceived or actually imposed constraints. From an economist's point of view, an altered choice situation is often caused by changing prices or incomes. Besides, the varied consumption of a particular product may be influenced by *multiple needs*, i.e. the altered use of a product by different household members, as outcome of a different usage situation (e.g. different location or different usage convenience) or simply by using a product for a different purpose. Second, varied behaviour may be implied *directly*, i.e. by changes in one's personal preferences. Those direct motivations for variety seeking may be categorised as (a) intrapersonal and (b) interpersonal. Intrapersonal motives might be *sensation seeking* and the desire for the unfamiliar, the alteration among alternatives of a perceived choice set as well as the (re-)acquisition of information about the previously chosen alternative or products (which the decision maker has not yet been in touch with). Finally, interpersonal motivations for variety seeking are often manifestations of uniqueness by satisfying individual demand by products which are potentially unavailable to other individuals (of the same peer group).

Table 2 Variety seeking: Motives

Derived variation (due to external factors)	Direct variation (preference related)
Changes in choice situation	Intrapersonal motivations
Changing feasible choice set	Sensation seeking – desire for the unfamiliar
Changing constraints	Alteration among familiar alternatives
Multiple needs	Acquisition of (new) information
Multiple users	Interpersonal motivations (exclusive choices)
Multiple situations	
Multiple uses	

Adopted from McAlister and Pessemier (1982)

According to these general motives of variety seeking, Timmermans (1990) identifies two types of behavioural models of consumption, which are denoted as "non-inventory based models" and "inventory based models". The first group of models usually excludes the particular properties of the choice alternatives as a potential determinant for choice. These models rather predict switching probabilities by past experiences the individual has with known alternatives. Consequently, typologies of decision makers are defined which categorise individuals into variety seekers and variety avoiders. Inventory based models on the contrary assume that there is an ideal point of consumption of the attributes of a choice alternative. "When consuming alternatives, the marginal utility first increases, but then decreases beyond the ideal points which reflect satiation" (Timmermans, 1990, 105). According to the above mentioned concept of a direct motivation for variety seeking, inventory based models allow for the preference for new experiences as well as intrapersonal and interpersonal variety.

However, Timmerman argues that none of both types may act as a satisfying explanatory models for destination choice: Whereas the non-inventory model does not allow to integrate modifications of the choice set or the single alternatives as result of a transport policy measure, in inventory models the assumption of a stable choice process would be queried "as policy decisions will almost invariably influence the process" (Timmermans, 1990, 111). Timmerman and colleagues (Borgers, van der Heijden and Timmermans, 1989) therefore formulated a model in which (a) choices are dependent on previous choices, (b) variety seeking behaviour is alternative specific and (c) a sophisticated approach to compare and value similarities as well as dissimilarities of attributes of alternatives is integrated.

3.3 Determinants of habitual and especially rhythmic patterns of travel behaviour

If travel is defined as a means to satisfy the demand for out-home activities, the question may be raised which factors influence the decisions to execute those activities and to combine them in larger patterns. The development of habitual behaviour needs to be seen as consequence of different psychological processes and environmental as well as social factors. Regularities in travel are predominantly influenced by temporal aspects of the social environment (such as fixed working hours, the sharing of tasks within the household, appointments etc.) and psychological aspects within decision processes. The latter factor refers to a range of situations in daily life (travel) where approved behavioural alternatives promise a relief from requirements of further or new decision making.

In the following, *generic determinants of time use and travel* as well as *specific determinants of periodic behaviour* are presented. The time budget or time use research offers a range of explanatory approaches to travel – with an origin in different scientific disciplines[5]. These include primarily space-time geography and behavioural psychology as well as economics.

Micro-economic theory of time-use and utility maximisation

Starting point for the micro-economic approach to explain time-use allocation is the fundamental assumption that households – similar to firms – need to be seen as production units (Becker, 1965; 1976). According to their potentials, they produce commodities such household related services which absorb financial and temporal resources.

Analogous to the theories of market behaviour of firms, private households may be imputed that when producing their commodities they equally follow the principles of cost minimisation on the one hand and utility or profit maximisation on the other hand. This implies that all activities underlie a (fictive) cost and utility accounting with an impact on human behaviour as well as on the scheduling and execution of daily activity patterns. Activities which yield a greater utility are therefore rated more valuable and will obtain higher priority for the personal time and activity planning.

A monetary aspect in time use is introduced with the assumption that the disposable income of households is a combination of the two components earned income (offering time to the la-

[5] An overview about conceptual and methodological intersections between time use research and travel behaviour analysis may be found in Bhat and Koppelman, 1999.

bour market) and lost income as a consequence of time use for household production, leisure or consumption. Hence, the disposable time budgets resolve into the two blocks *productive* time (since wage generating) and household related *reproduction* time. This theory allows to conceptualise behavioural models which for example quantify the impacts of pay increase on the allocation of time or the relationships between rising prices for goods or services and their substitution by reproduction work.

Recognising the straightforward approach which imposes activities a monetary assessment, time use research itself has questioned the underlying assumptions (see e.g. Juster and Stafford, 1991; Pollak, 1999), for example

- the definition and the observability of commodities (What about household related activities that do not produce measurable outputs?),
- the assumption that households have a common household utility (instead of several individual utilities for different activities) or
- the presumption that every household related activity generates the same utility for an individual and that there are no taste differences for the different housework types between individuals.

Space-Time-Geography and related approaches

Most of the explanatory approaches to analyse and forecast personal time budgets are based on classical theories of *space-time-geography* developed by the *Lund School* (Hägerstrand, 1970; Carlstein, Parkes and Thrift, 1978)[6]. Besides, related concepts exist which try to describe the development of human activity patterns (Chapin, 1965; 1974; 1978; Heidemann, 1981; Beckmann, 1983). The fundamental linking principle of the approaches is the idea that human behaviour is embedded in a complex system of personal as well as external restrictions. The set of restrictions or *constraints* travellers are exposed therefore shapes their individual *decision space* for time use and activity execution.

The constraints originate from a range of needs and requirements for human interaction as well as cultural, legal and organisational conventions and rules. Hägerstrand (1970) defines three main categories of constraints which are embedded in a close network of interactions and which together shape the personal activity potentials of travellers:

[6] (Space-)Time geography (*chronogeography*) emerged out of research undertaken in the late 1960s and 1970s, by Torsten Hägerstrand and his colleagues Tommy Carlstein, Bo Lenntorp and Solveig Mårtensson, a group of Swedish geographers based at Lund University - who became known as the 'Lund School'.

- *capability constraints*: individual biological and physiological needs such as sleep or eat, the physiological possibility or restrictions to move, the availability of and access to mobility tools, temporal and financial resources to conduct activities and make trips,
- *coupling constraints*: restrictions for an autonomous allocation of time due to the need for coordinating with institutional settings (schedules or given locations) and the interactions with other individuals (appointments or meetings with other household members, relatives, friends, business partners etc.)
- *authority constraints*: formal and informal rules or norms of economic or legal character such as opening times, balance of powers etc.

Furthermore, the Lund School associates each activity with a space and a time aspect which are intrinsically tied to each other. The model represents space-time graphically as a three-dimensional system where space opens up a two-dimensional plane and time forms a vertical axis on this plane (Figure 5). The sequence of activities of a traveller over a defined period of time (day, week, life etc.) may be visualised as path through the system with movements implying a coordinate change in space and time.

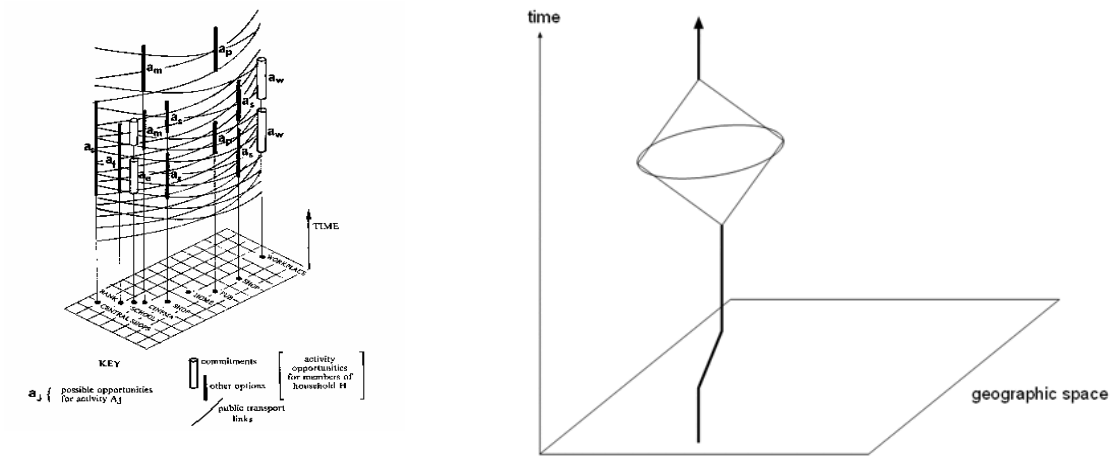
Figure 5 Time geography: concept and application (right: realised space-time path example in 3-D space)

Keßler (2006) Kwan (2006)

The constraints may be seen as concentric tubes if this graphical concept is added by the set of described restrictions (Shapcott and Steadman, 1978). The tubes narrow the temporal and spa-

tial degree of freedom for example by the allocation of certain obligations (such as the activity *work*) in fixed time and/or space bandwidths (Figure 6). Besides the inflexible or fixed activities disposable time remains which is represented as a prism in the model. The prism's size (characteristics) is predominantly given by the individual travel potentials such as one's physical fitness, mobility tool availability or the location of for example household and workplace.

Figure 6 Impact of constraints on the space-time path and the degree of spatial and temporal freedom (prisms)



Adopted from left: Jones, Dix, Clarke and Heggie (1983) 44/45, right: Keßler (2006)

In the context of urban planning, Chapin develops a multi-stage model to represent activity systems in cities, in particular in his 1974 book *Human Activity Patterns in the City*. Chapin pays particular attention to the interactions between the activity patterns of persons or households and the aggregate processes within (urban) institutions such as firms, public authorities or schools.

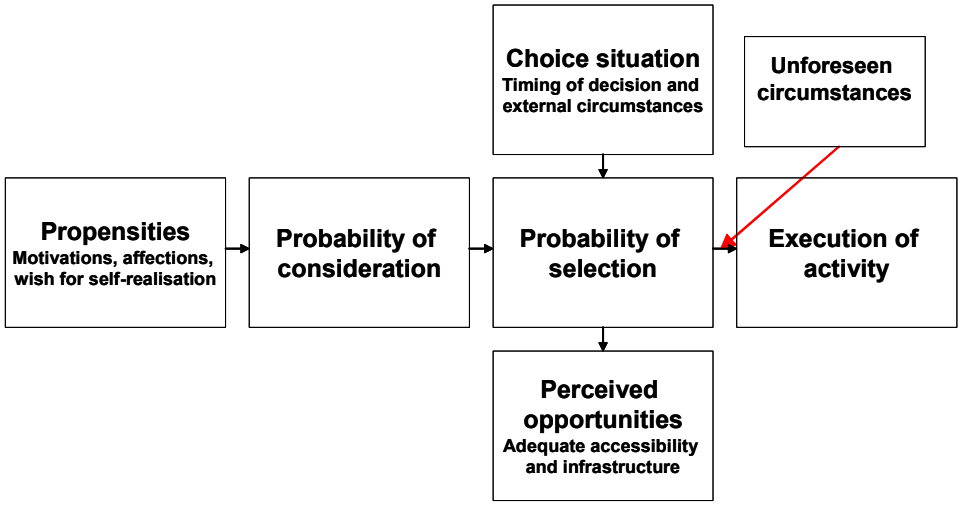
The decision process of activity scheduling and execution is described as a three component system with the following elements:

- motivation to execute an activity,
- choosing a potential option to satisfy demand and
- the result of the decision process (Chapin, 1978).

The probability to choose and to execute a particular activity is determined by *personal propensities*, the situative temporal frame/background of the decision and the perceived spatial *opportunities* connected with activity.

Individuals develop propensities based on their motivations and attitudes whereas they assess spatial opportunities by their perceptions of the accessibility and the quality (equipment) of given locations. In contrast to the Lund School, a stronger focus is put on the individual perception of one's environment. Besides, equally important is the evaluation of the situative context of the activity or travel choice.

Figure 7 Human Activity Patterns in the City: Model of decision making processes



Adopted from Chapin (1978) 15

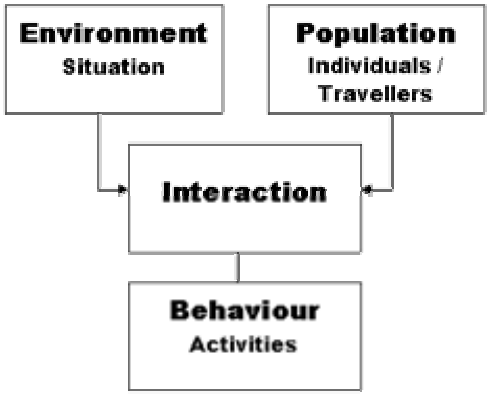
Socio-ecological approach

Based on theories from the research into ecosystems, Heidemann develops his *socio-ecological approach* to explain activity and travel behaviour (Heidemann, 1981). The approach defines human behaviour as a result of the interactions between individuals (and households) with their environment – in particular with the technical and social infrastructure. The interaction between the demand side (individuals/households) and the supply of opportunities (built environment/infrastructure) lead to decision/choice situations which relate the

needs of an individual with the opportunities/potentials of his/her surrounding environment. The outcome of this decision process is individual spatial behaviour which induces movements and therefore travel.

Similar to the Lund School, it is assumed that different restrictions have a regulative impact on the spatio-temporal behaviour – Heidemann introduces the terms *regimes* and *budgets*. Regimes capture general rules and laws and their effects for the organisation of the society. Budgets are defined as the personal and/or group-specific potentials and capacities to maximise utilities. Societal as well as personal constraints are categorised as *time constraints*, *means constraints* and *information or knowledge constraints* – which is a structure similar to the one proposed by Hägerstrand.

Figure 8 Socio-ecological model of space-time behaviour (basic approach)



Adopted from Heidemann (1981) 292

Homogenous groups of behaviour

Kutter stresses the socioeconomic attributes of the traveller as explanatory determinants for their time-use and travel behaviour (Kutter, 1972; 1973). This categorisation of persons into homogenous groups is one of the predominant explanatory approaches for complex activity patterns and is widely applied in forecasting models (see also Lammers and Herz, 1979; Schmiedel, 1984; Schlich, 2004). A similar concept is developed in Harvey (1982).

As theoretic foundation of the concept, Kutter refers to *role theory*[7] which has strong roots in psychology and sociology. Role theory explains behaviour as an outcome of social learning processes. Individual behaviour is believed to be embedded in fixed and predefined structures which are mediated in institutions such as school or family. People tend to adapt to these structures with a high probability. Based on these assumptions and in consideration of so called *key roles*, Kutter categorises the population into different homogenous groups of behaviour with a high degree of socioeconomic similarity. The groups are mainly built using the attributes occupation (status), sex and availability of a personal vehicle.

Again, the concept of roles or group affiliation is methodologically closely connected with the theories of space-time geography. The *main activity* associated with the respective group (such as work) has a dominant impact on the time-use and activity scheduling as it widely determines the travel demand of daily life. This approach which is highly pragmatic in terms of a predefinition of travellers by mainly occupation status has been discussed critically in many later travel behaviour studies (see Volkmar, 1984; Schlich, 2004). One of the implications which were discussed most critically is the question whether behaviour remains constant and/or consistent just because a traveller is assigned a main obligatory activity such as work or education. Finally, Schlich (2004) could show that from a longitudinal perspective – which is the background of this study, too – travel behaviour and time use within pre-defined homogeneous groups is by far more variable than the underlying assumption based on cross-sectional data analysis would allow for.

Social network approaches

Social networks – as an expression of the embeddedness of people in a network of personal contacts and surrounding societal settings – have been examined for long by social scientists from a range of perspectives (Larsen, Urry and Axhausen, 2005):

- a community approach which stresses the belonging of people to a group of peers defined by geographical propinquity, a systematic social interrelationship or close personal ties (such as friendship or family) (Bell and Newby, 1976)
- a Social Network Analysis (SNA) approach which focuses on the "structural properties that connect people in webs of friendship, mutual support and sociality through face-to-face talk, phone conversations and emailing" (Larsen, Urry and Axhausen, 2005, 23) (see e.g. Scott 2000, for a UK focussed review) and

[7] See for an overview Wiswede, 1977.

– a Small World approach (see Urry 2004 for an overview) which tries to systematically analyse the so-called 'small world phenomenon' (see Urry, 2004) which postulates that everybody in this world is separated only six degrees of separation from anybody else.

Only recently, social networks were introduced as a new possible predictor of travel behaviour and movement. Researchers such as Urry and others (see e.g. Sheller and Urry, forthcoming) argue that flows and meetings of objects, technologies and especially people produce small worlds which require connections and meeting places. A new social network (analysis) approach which is called "mobilities" discusses and investigates how the traffic between those places is organised by, on the one hand, traditional *mobility tools* (Axhausen) such as cars or aeroplanes and, on the other hand, network tools such as letters, email or the internet.

> "Central to networks are the forms and character of the meetings and hence of travel in order both to establish and to nourish links or at least temporally cement them. Instead of focusing upon the formal structures of the networks themselves, this mobility approach analyses the embodied making of networks, performances and practices of networking. Social networks come to life and are sustained through various practices of networking […]" (Larsen, Urry and Axhausen, 2005, 28ff.).

With this understanding of social networks as a facilitator of virtual as well as physical networks and the movements within them, travel – as one mean of satisfying movement requirements – becomes a results of human networking. Travel demand of all forms (especially work, business, and leisure etc.) therefore mirrors the embeddedness of people in professional and private communities which develop needs for meetings at various close or far-off places.

Specific determinants of the habitual behaviour and periodic elements of activity demand

In the context of this thesis, the above description of the general determinants of travel behaviour needs to be complemented by explanatory approaches which in particular focus on the habitual character of travel:

Habitual travel behaviour – the re-use of behavioural alternatives in similar choice situations – is widely seen as a human strategy to cope with the complexity and the variety of the urban travel environment (Gärling and Axhausen, 2003). Cullen (1978, 33) states:

> „The point is that the process of adaptive routinization may be viewed as an entirely rational response to a highly complex situation. It is a way of negotiating a

> tortuous path through a difficult environment and a wealth of commitments. Repetitive deliberation and choice are impossible luxuries when it comes to day to day living in a post-industrial city."

Equally important for the routinisation of daily life is the question how travellers process and use the growing amount of information about the temporal and spatial context of the trip making. Sure, the possibility to decide for a (new) alternative option for example in route or mode choice is essential to escape the boredom of quasi mechanical behaviour – this requires however the operationalisation of acquired knowledge and information of temporal and spatial circumstances (Huff and Hanson, 1986).

Two of the most frequently mentioned psychological concepts which foster the development of behavioural routines are *Bounded Rationality* and *Cognitive Maps*:

Despite the above mentioned assumption that people tend to act in utility maximising way when using their resources (time, income etc.) it is likely that– from a neutral point of view – the "best alternative" is chosen only rarely. This is especially not the case if decisions need to be made quickly or if decision has only little priority. In most cases the chosen alternative deviates from the optimal one – relative to the cost-benefit expectation of the choice or its importance. This behavioural strategy is known as *Bounded Rationality* (see Simon, 1957 for an introduction into the terminology of rational choice). In a more general context of economic behaviour, travellers often show satisficing behaviour instead of being entirely rationale and search for an optimal solution.

The acceptance of satisfying solutions has the consequence that in the past adequately successful (routine) behavioural elements are chosen in order to avoid further complexity in the decision making process as well as additional search, organisation or evaluation of relevant information.

The often insufficient availability of additional information which would be necessary to solve problems optimally and the individual restrictions of cognitive processing capacities are further casuals for preferring known behavioural alternatives. The quality of information of travel options such as accessibility, network structure or capacities has an important impact on the discrete choice of mode, route, departure time etc. (Schofer, Khattak and Koppelman, 1993). The decision space as well as the probability that travellers deviate from a known (satisficing) alternative increases with a greater availability of exact, contemporary and understandable information.

In addition to that, people usually apply simple rules (heuristics) to make decisions and combine their (passively) memorised experiences and their actual knowledge to decide on long-term (e.g. car purchase) or short-term options (e.g. departure time of a trip) (Simon 1979; Schofer, Khattak and Koppelman, 1993). As the combination of available knowledge and additional information may complicate the decision situation, human beings try to simplify the substance of information in order to make many decisions in shortest time (see Kahnemann, Slovic and Tversky, 1982). The result of such heuristics is often the reapplication of previously successful behavioural solutions.

Habitual travel behaviour is finally caused by the imperfect knowledge about the spatial environment and the limited set of known alternatives in space – for destination as well as route choices. Travellers usually face mental capacity restrictions. The perception and the operationalisation of spatial information within cognitive processes obviously restrict the capacity of mental representation as well as the resolution of networks or the built environment (see Downs and Stea, 1977; Lynch 1960). As could be shown in several experiments (ibid.), the representation of one's surrounding environment is biased and not therefore entirely complete. The physical environment seems to be memorised and processed in *mental* or *cognitive maps*, which do not allow a scale accurate, comprehensive and error less representation (see Downs and Stea, 1977; Lynch, 1960; Gould and White, 1986).

Cognitive maps have a considerable impact on travel choices as they supply the set of alternatives for all day-to-day but also long-term mobility related decisions. For example, congested roads or areas can only be bypassed if there is sufficient spatial knowledge and representation to positively evaluate alternative routes which are potentially less congested or not congested at all. It could be shown that there exist great differences between travellers for in understanding and final usage of spatial information. This finally has implications for the extent people behave routinised or with a higher degree of variability.

3.4 Earlier investigations of variability and stability in travel behaviour – a (compact) literature review

As mentioned above, the analysis of the regular structures in individual travel behaviour is not a new issue; however this has been limited so far by the rarity of multiday mobility data which would permit the detection of periodic structures. Clearly, cross-sectional data can be used as well and was in fact used to provide insights into the regularity of (overall) mobility

patterns (e.g. Herz, 1983), but as this thesis focuses on the variability of individual behaviour over time the cross-sectional perspective is neglected here.

The earlier investigation of the intra-personal variability is tied to the few multiday data sets such as the Cedar Rapid movement study (Garrison, Berry, Marble, Nystuen and Morrill, 1959), the Uppsala Household Travel Survey data of 1971 (Marble, Hanson and Hanson, 1971) (see also next chapter), the Hamilton-Wentworth travel diary with its two week duration (Webber, 1978), the 7-day Reading activity data set (see e.g. Pas, 1980) or the Austin area 10-days commutes data set collected 1989 (Mahmassani, Hatcher and Caplice, 1992). A more recent analysis approach to reveal regularities in travel behaviour used the Lexington 1996 GPS feasibility study data (six consecutive days) (Batelle Transport Division, 1997).

The 1949 Cedar Rapid movement study covered a sample of 262 households in Cedar Rapids and surrounding areas (Iowa/USA) (Garrison, Berry, Marble, Nystuen and Morrill, 1959). The travel diary (all modes) was designed for a 30 consecutive days reporting period for all household members 10 years and older. The later analysis was based on smaller subsamples and focused on the spatial regularity and extent in travel behaviour – especially in shopping (ibid.; Marble and Nystuen, 1968; Marble and Bowlby, 1968). In summary, the investigation revealed considerable spatial stability with about three quarters of all destinations being frequented repetitiously. Besides, the intensity of chaining trips was found to be great for city centre shopping and weak for grocery shopping.

Susan Hanson and collaborators focused their analysis of the Uppsala Household Travel Survey on the habitual characteristics of travel behaviour (see e.g. Hanson and Huff, 1982, 1986, 1988a, 1988b; Hanson and Burnett, 1981; Burnett and Hanson, 1982; Huff and Hanson 1986, 1990). They found that isolated elements of travel behaviour can be found on a distinct periodic basis if individuals are observed over prolonged periods such as several weeks (Hanson and Huff, 1986; Huff and Hanson, 1986). In addition, the researchers developed measures for the extent of day-to-day variability for single travellers as well as for the stability of individual behaviour over the entire survey period of the UHTS using some selected features of activity demand and trip making (e.g. a combination of purpose, time of day, mode etc.) (ibd.). The analysis of these indicators – which were interpreted as *similarity indices* for regular trips and *representative days* – led to the conclusion that in average there is only little behavioural similarity between the different days of one single traveller – even if the five most representative daily patters for each person are considered (Hanson and Huff, 1988). The work started a discussion about the usefulness of the representative day assumption for transport modelling approaches based on cross-sectional travel survey data. As already mentioned, the non-

existence of typical days for individuals questions the postulate of a behavioural equilibrium for single travellers which is implied in most of the common models till now.

In his early work, Pas developed indicators to classify daily travel behaviour by similarities using the 1973 Reading 7-day activity data set (Pas, 1980; 1983) – analogous to the studies of Hanson and her collaborators. In the following, Koppelman and Pas (Koppelman and Pas, 1984; Pas, 1986) provided support for Hanson's sceptical view on trip-generation models entirely relying on one-day travel data. They found a considerable bias between the trip rates predicted based on regression models using cross-sectional and longitudinal data. Pas (1987) investigated the variance in daily trip rates of single travellers and used the outcome as a measure of day-to-day variability in travel behaviour. He found that about the half of observed total variability in samples could be explained by *intra-personal variability* which needs to be conceptually separated from *inter-personal variability* which describes the differences in e.g. trip rates between travellers (see discussion above).

Pas and Sundar (1995) employed a three-day travel data set from Seattle (1989) for the analysis of a range of mobility indicators such as trip chaining and daily travel budgets. Similar to the Reading results, it was found that a substantial share of the overall variability observed within the sample is caused by intra-personal variability.

Bhat (2000a; 2001) investigated the intra-personal variability of mode choice and stop making behaviour for commute trips using the three (five)-day San Francisco Bay Area Household Travel Survey data (White and Company, 1991). Among other things, the results strongly recommend to incorporate heterogeneity aspects in mode choice models for consecutive panel data. This allows only to capture behavioural variations as they may not be explained sufficiently even by the best systematic specifications of the models.

Mahmassani and colleagues put a focus on the day-to-day dynamics of travel behaviour (Chang and Mahmassani, 1989; Hatcher and Mahmassani, 1992; Mahmassani, 1997; Mahmassani, Hatcher and Caplice, 1997). The researchers analysed the departure time choice, trip chaining and route choice for morning as well as evening commuting trips (Mannering and Hamed, 1990) based on laboratory experiments and the Austin/Texas multi-day survey. An interesting result of their work was that there are stronger propensities or elasticities for changing behaviour for route compared to departure time choice.

The Lexington GPS study is one of the first multi-day travel data source not entirely based on traditional PAPI (paper and pencil interview) or CATI (computer assisted telephone) survey

design but augmented by a (in-vehicle) Global Positioning System (GPS) devices and Geographic Information Systems (GIS) (see also Chapter 4) (Batelle Transport Division, 1997; Pendyala, 1999). The study yielded (car) travel behaviour information for up to seven days. The studies based on that data source focused on variability issues such as repetitive behaviour (Pendyala, 1999) reapplying e.g. Pas' methods to reveal the share of intra- and interpersonal variability and on day to day, or one day-of-week to another day-of-week comparisons (Zhou and Golledge, 2000; Muthyalagari, Parashar and Pendyala, 2000). The results were in line with earlier findings on the variance in individual mobility (such as Pas, 1987) but also stressed the importance of the weekday as a determinant for trips distance, frequency, purpose, direction, and the type and temporal characteristics of activities.

The Mobi*drive* data (Axhausen *et al.*, 2000) – which is one of the main data sets to be investigated in this thesis – received considerable attention in terms of the analysis of behavioural regularity, rhythms and their determinants. The econometric investigation differed in the selection and the complexity of the model approaches as well as in the objective of analysis. Schönfelder and Axhausen (2000, 2001) as well as Fraschini and Axhausen (2001) focused on daily rhythms in general using common Survival and Time Series Analysis methodologies. Bhat, Sivakumar and Axhausen (2003) analysed the impact of information and communication technologies on long-term-shopping intervals by an advanced hazard-based model incorporating sample selection, random coefficients and unobserved heterogeneity issues. Bhat, Frusti, Zhao, Schönfelder and Axhausen (2004) had a look at the temporal structure of grocery shopping applying a latent segmentation method. And finally Bhat, Srinivasan and Axhausen (2005) highlighted the structure of weekly inter-activity performance using a hazard model covering several complex modelling aspects such as flexible duration dynamics structure, variation in interepisode duration due to unobserved individual-specific factors and variation in interepisode duration. All models yield interesting findings on the structure of activity demand which – although the weekly periodicity dominates – differs considerably for individual travellers due to their socio-economic backgrounds and preference structures.

Many of the analyses applied to the Mobi*drive* data were repeated within the framework of the Swiss SVI Stabilität research project with a comparable 6-week travel diary concept (Thurgau data, see below). The results can be found in Löchl, Schönfelder, Schlich, Buhl, Widmer and Axhausen, 2005.

3.5 Destination choice

(Human) Geography has always had a strong interest in movement patterns of people and has put forward the question of where people head and how people decide on where they go in countless conceptual as well as empirical studies. Destination choice may be discussed from at least two perspectives within the context of travel, i.e. the long-term locational choice issue (residential location, workplace location, location of firms etc.) and the short-term perspective of day-to-day travel for shopping, service, business or leisure.

Transport modelling has operationalised the latter aspect – which is key for this study – applying aggregate as well as demographically disaggregate approaches. Aggregate trip distribution models widely rely on the well-known *gravity model* which goes back to *Newton's law of universal gravitation*. The law states that "every object in the Universe attracts every other object with a force directed along the line of centres of mass for the two objects. This force is proportional to the product of their masses and inversely proportional to the square of the separation between the centres of mass of the two objects" (URL: http://en.wikipedia.org/wiki/Law_of_universal_gravitation). Transferred to travel analysis the model represents the aggregate relationship between (two) places or zones and their interactions with each other. The level of interaction basically declines with increasing distances and increases with the "amount of activity at each location" (Isard, 1956). The gravity model in its simple original form is still the base for a range of trip distribution models – however, it was refined and complemented (for example by the aspect of inner-zonal traffic) at many places for about 80 years now (see e.g. Reilly, 1929; Stewart, 1948; Ruiter, 1967; Wilson, 1967 for early examples). The major drawback of the early applications of the gravity model to destination choice is the fact that they inherently produce great streams for nearby places and therefore prioritise short-distance OD-relations. Consequently, the original model neglects the advantage of walking over mechanical modes for short trips. Besides, the basic model considers same ratios of costs (travel times) equally irrespective of the absolute values, i.e. 5 min / 10 min = 50 min / 100 – which is unlikely in realistic choice situations. Modern transport modelling software makes use of more sophisticated impedance functions which consider destination choice not only as a function of distance but also as interrelationship of distance (trip distribution) and mode choice (e.g. Lohse, 1997 (*EVA-Funktion*)). The drawback of aggregate models in general (a similar approach is the *intervening opportunity model* by Stouffer, 1940) is the lack of an appropriate representation of human behaviour and decision making ("Zones don't travel; people travel!"). With the emergence of discrete choice techniques, demographically disaggregated approaches were introduced which consider other variables than purely

travel time (mediated by interzonal distances) such as in the gravity model (Ben-Akiva and Lerman, 1985)[8]. However, for travel analysis and transport planning destination choice remains one of the key challenges for analysis and strategy development as compared to the choice situations such as modal choice, route choice or departure time choice, (discrete) choice models have for long not captured the complex underlying decision processes in individual spatial choice (Hunt, Boots and Kanaroglou, 2004). Some researchers have even argued that choice models are not appropriate for the analysis of spatial choice (Fotheringham and O'Kelly, 1989) (which was probably true for the first approaches to apply choice models to destination choice), but the methodological development in this field over the last twenty years has shown substantial progress (see e.g. Fotheringham, 1983 for early or Bhat, 2000a; Bhat and Zhao, 2002 for more recent examples). The most important advance in the understanding of destination choice and its modelling was certainly that the rigid substitution pattern based on the independence of irrelevant alternatives" (IIA) property in MNL (Multi Nominal Logit) models do not correspond with choices for destinations. Some places might better substitute others than competing alternatives within the given choice set due to their particular characteristics of size, dimensionality, spatial continuity, neighbourhood to other sites and so on (Haynes and Fotheringham, 1990).

Choice set formation is another critical point in destination choice by discrete choice approaches. As the number of possible alternatives in a destination choice problem can be and often is considerably larger than in other travel choices such as mode choice, there is a great danger of an incorrect estimation of model parameters and therefore incorrect prediction of choices by a misspecification of the choice set (Manski, 1977). Thill (1992) describes several strategies to formulate choice sets by (conceptual) assignment:

- Defining universal choice set – all possible destinations are considered (Problem: goes far beyond the actual considerations of an individual) (Ben-Akiva and Lerman, 1985)
- All individuals are assigned the same choice set which capture all destinations in the area of interest (most often applied)
- Destination-specific choice set definition: a perimeter is set around each location in the universal choice set; distance threshold is due to relative gains and losses in predictive power that would result from excluding destinations in specific distance classes from the choice set (Problem: choice set is a function of the choices mod-

[8] It should be mentioned that discrete choice models for destination choice (in a logit form) and the gravity model do not necessarily contradict as they show broad similarities ("entropy maximisation model"; Wilson, 1967).

elled which would result in a simultaneous equations bias) (Black, 1984; Parsons and Hauber, 1998)

- Choice set of an individual consists of all destinations that were actually chosen by individuals living in the same area (Argument: people living in the same area are constrained in a similar way, are affected by the same spatial structure of the urban environment and are familiar with the same shopping or recreational opportunities)
- Choice set generation modelled by algorithms which simulate human learning (Meyer, 1980)
- Preference ranking of destinations by asking the respondent (stated preference method) (does not allow for any substitution among attributes which would allow an overall favourable ranking even if one attribute is ranked poorly) (Arnold, Oum and Tigert, 1983)
- Information about individual choice set is directly obtained from the decision maker by naming potential alternative destinations and their actual choices (Problem: people appear not to be able to report their choice sets accurately) (Lerman, 1983)
- Two-stage choice set generation: Joint modelling of choice set and choice (Manski, 1977) and choice set as an outcome of an additional discrete choice model which endogenously generates alternatives (Zhang, Fujiwara, and Kusakabe, 2004).

The question of how to generate choice sets in destination choice is touched at this stage to the understanding of specific detail as it is believed that the analysis of longitudinal data will add somehow on the size and structure of choice sets in spatial choice. As this list shows, the generation of choice sets is widely driven by researcher's pre-assumptions about likely choices, search area boundaries or potential homogeneous search behaviour. This question will be raised again at the end of this thesis.

3.6 Spatial behaviour and activity spaces

Spatial behaviour analysis as a broader concept than destination choice stresses the interaction between individuals and their surrounding environment and goes beyond the question of actual choice.

Human geography, sociology and other related disciplines have developed concepts to represent, analyse and model location and destination choice as well as the usage of urban space. The approaches were of both, aggregate and disaggregate character, i.e. with a focus on the average distribution of places frequented and an individual perspective of a person's or

household's mobility. Not all of the approaches are conceptually, only, as where suitable data or surrogate information was available the models were tested.

Conceptual approaches

One of the first aggregate approaches to estimate people's range of movement and contact is Hägerstrand's *Mean Information Field* (MIF) (Hägerstrand, 1953). In brief, the MIF gives the average spatial extent of a person's short-term contacts. The conceptual idea of the calculation is simple: From a given centre of a coordinate system, a series of rings is drawn and the number of points of destination/termination in each ring is tabulated. Based on this distribution a Pareto curve is fitted of the form $Y=aD^{-b}$, with Y is the expected number of persons per square kilometre and D is the distance from the point of origin in kilometres. A cell grid is the constructed and the estimating equation is taken to give point estimates of the expected amount of people in each of the exterior cells. Dividing each cell entry by the sum of all cell values gives the respective probabilities. As Hägerstrand and his colleagues could not use longitudinal movement information which would have fulfilled the research requirements, they used local migration data to test the model. The concept was applied to other data sources and in different contexts later, interestingly also to one of the first longitudinal travel data sets ever, the Cedar Rapids movement study data (Garrison, Berry, Marble, Nystuen and Morrill, 1959; Marble and Nystuen, 1963).

Lnych's work (1960) on *cognitive or mental maps* (see also above) focuses on the assumption that the perception of space is a highly subjective process – in contrast to the generalised representation of space in cartography. Based on the interest in the relationship between the structures as well as quality of architecture and human perception, Lynch found out that the mental maps of individuals, i.e. the image which human beings develop about their (travel) environment, are

- more or less biased
- are simplifications of the real world
- group-specific and
- composed of about five basic elements which have different meanings for the structure of urban space in different cities (paths, border lines, areas, foci and landmarks).

Mental maps mainly act as an individualised cognitive support for spatial ordering and orientation. Mental maps and their formation may methodologically be captured only indirectly – Lynch used memory protocols and - as a main approach - map sketches of test persons. As

mental maps have a great potential to "test" the acceptance, efficiency and clarity of urban design for users and citizens, the methodology has been widely applied in space related scientific disciplines. Besides, Lynch's idea was the starting point of a conceptual dispute in human geography as the mental maps approach partly questions the common behavioural perspective in perceptive geography (*stimulus-response-relationship*) (Anderson, 2000).

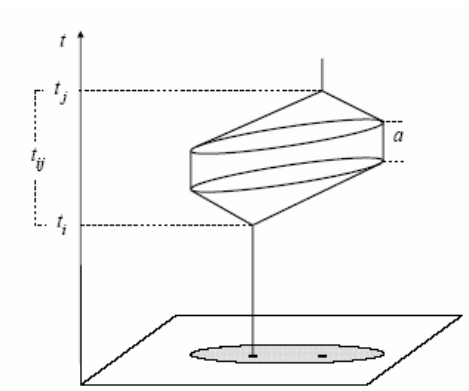
In a wide sense, the action space concept by Horton and Reynolds (1970) and others comprises both those locations of which a traveller has personal experience, as well as the knowledge space of locations, of which the traveller has second hand experiences through family, friends, books, films or other media. Jakle, Brunn and Roseman (1976) summarise the action space concept as the total interaction of an individual with its surrounding social and built environment and comprises all those places in which people potentially operate. Another approach to action space is the idea of an individual evaluation of spatial alternatives: Each possible destination is assigned a place utility which yields a degree of satisfaction or dissatisfaction when considered or chosen. The action space as a whole may be seen as the sum of those utilities (see also Wolpert, 1965). Linking the perceptual space approach above with the idea of action space, action space may be defined as a part of the perceptual (cognitive) space whose particular locations the traveller does not only know but also potentially chooses as a destination alternative (Dürr, 1979). This definition is closely connected to the principles of space-time-geography which considers travel behaviour as an outcome of a complex system of individual and external constraints (Hägerstrand, 1970).

Dürr (1979) also adds on the phenomenon of selective perception of spatial structures and the idea of the *perceptual space*. In contrast to a universal representation of an action space, the perceptual space captures an incomplete section of the objective environment. Individuals select that information from their surroundings which appears important for the satisfaction of needs and achievement of their objectives. This resulting perceptual space may be seen as a biased mental map in line with Lynch's as well as Gould and White's (1986) work.

Inspired by Hägerstrand's space-time paths (see above), Lenntorp (1976) – a member of the Lund School – developed the concept of space-time prisms. He operationalised Hägerstrand's ideas towards a measure of individual accessibility based on the notion of a person's reach. Space-time prisms define the possible locations for a space-time path with obligatory activities such as work fixing the shape of the prism by predefining the person's location. Figure 9 gives an example for a fictive prism (Miller, 2004): The two anchor points represented in Figure 9 are home and work place with a given minimum (fixed) departure time t_i and a maximum arrival time at work t_j. The gap between those times is planned to be used for an-

other activity at some location which needs at least *a* time units. In addition, the fictive traveller is able to move with an average maximum speed *v*. The interior of the prism is called the *potential path space* and contains all points in space and time that the traveller is able to reach within his or her travel episode. A traveller will not have the chance to execute an activity unless its space-time path (reflecting its location and available times) intersects the potential path space sufficiently. The projection of the potential path space to geo-space gives the *potential path area* which consists of all locations that the person could potentially occupy. A traveller cannot participate in an activity unless its location is part of the potential path area (ignoring the temporal duration of activities).

Figure 9 Example of a space-time prism



Source: Miller, 2004

The activity space approach and the daily level

Finally, the *activity space* concept – which was developed in parallel with several of the approaches presented above to describe individual perception, knowledge and actual usage of space in the 1960s and 1970s (see Golledge and Stimson, 1997 for a discussion) – aims to represent the space which contains the places frequented by an individual over a period of time. Activity spaces are (geometric) indicators of the *observed* or *realised* daily travel patterns (see also Axhausen, 2002). This is stressed here as the related concepts such as *action space*, *perceptual space*, *mental maps* or *space-time prisms* mainly describe the individual potentials of travel. An activity space is here defined as a two-dimensional form which is constituted by the spatial distribution of those locations a traveller has personal experience (*contact*)

with. Important geographical reference points of the activity space usually are home and the most important other regularly frequented locations. Consequently, activity spaces are mainly the result of

- the position of the traveller's home location,
- the duration of residence,
- the supply of activity locations in the vicinity of home,
- the resulting neighbourhood travel,
- mobility to and from frequently visited activity locations such as work or school and
- travel between and around the centres (pegs) of daily life travel.

Especially the *home location* is often emphasised as a "pocket of local order" – i.e. as a principal anchor point of time use daily travel (see e.g. Ellegård and Vilhelmson, 2004). Subsuming further – rather sociological –characteristics of activity spaces, Jakle *et al.* (1976) give the following definition:

- Activity spaces are manifestations of our everyday lives.
- They may be defined as an important process through which travellers gain information and attach meaning to our environment.
- Activity spaces are linked to the concept of *territoriality*, i.e. the direct contact with locations has an influence how we define territories or habitats.
- The movement between places is related to perceived territories.
- Activity spaces refer to one's role within society and are therefore linked to personal (socio-economic) attributes and group affiliation.
- An individual activity space is product of one's definition of a set of activities one wants to participate.

Finally, activity spaces underlie fundamental geographical principles such as *distance decay* and *directional bias* (ibid.) which implies that the probability of (regular) contact with a location usually decreases with its distance from the peg(s) of daily life (i.e. in particular home) and the deviation from the main orientation / direction of daily travel. The latter refers to preferences for a particular place over other places of equal/similar distance due to some perceived quality of the preferred place (Golledge and Stimson, 1997).

3.7 Earlier empirical studies on locational choice and activity spaces

Empirical work on revealed activity spaces – above all by longitudinal travel data – is rare. Where such studies have been made, they were mostly focused on travel potentials or opportunities referring to action space analysis.

The earlier literature on the actual estimation and measurement of activity spaces is mainly based on cross-sectional data for groups of respondents. Treating many cross-sections as a quasi-panel of an average person (type) is problematic, as it ignores the biographical elements in the mental map of an individual and is likely to bias the conclusions.

One of the rare studies on locational choice using multi-day data was undertaken by Marble and Bowlby (1968). Applying an enumeration and listing approach to the Cedar Rapids travel diary data (30 day-period), the researchers found great stability in destination choice on the daily level. About three quarters of all trips were made to 'repetitiously visited locations' with about 25% to 50% of these trips for shopping purposes. Interestingly, the sensitivity to distance decay was lower for trips to regular destinations which opens up the discussion on the particular characteristics of habitual spatial behaviour and variety seeking (see below).

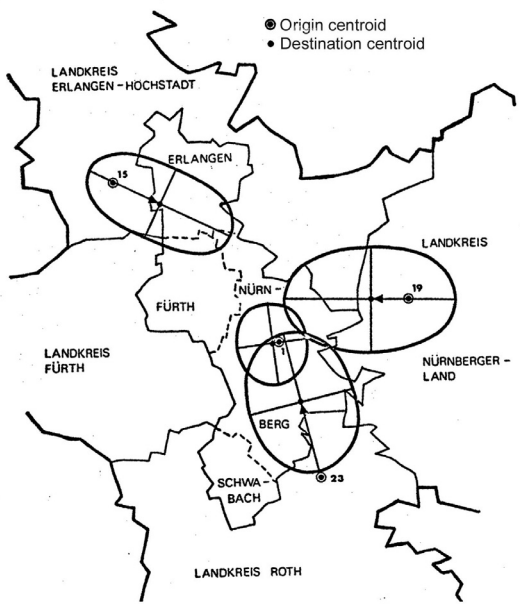
In another early study Kutter (1973) linked his hypotheses on the stratification of the population by groups of homogenous travel behaviour (see above) with the question where those groups execute activities and how spatial usage intensities vary according to personal attributes. Based on a small (cross-sectional) sample from the city of Braunschweig (Germany), he investigates the spatial distribution of activities by area type, lifecycle group and distance from home. The study – considering the low car availability and usage rate for Germany – confirms the assumptions of a strong correlation of distance decay for activity intensity, however, with different sensitivities for different activity types, the importance of home as an important anchor point of daily life and the different activity space sizes for different socio-economic groups.

An aggregated perspective of urban and regional space usage and travel densities is provided by the 1970s UMOT project (*Unified Mechanism of Travel*) and subsequent studies (Zahavi, 1979; Beckmann, Golob and Zahavi 1983a; 1983b). One focus of the UMOT project was to analyse densities of activity locations (or trips) and to test hypotheses about the character of trip distributions at the regional level given a certain mode choice and the spatial structures of the regions studied. This work was based on one-day travel diaries. UMOT lead to the calculation of ellipse shaped *travel probability fields* which are the geometric result of travel de-

mand, network structure (system supply) and the supply of activity opportunities (urban form) (Figure 10). The major findings were that

- the fields' directions tend to be towards the urban cores,
- the length of the fields are proportional to the distance of the zone's centroid to the main agglomeration centre,
- there are differences of shape between the different modes of transport and
- there exist strong relations between the infrastructural supply of the region and the direction of the probability fields.

Figure 10 Travel probability fields in the Nuremberg region



Source: Zahavi (1979) 230

Scheswig (1988) analyses the importance of the axis home-work based on activity and destination choice frequency data collected for the Hamburg region beginning of the 1980s (see also Dangschat, Droth, Friedrichs and Kiehl, 1982). The study is one of the few earlier investigations using quasi longitudinal data covering a period of one month.

With a focus on the integration of complex travel patterns into concepts of accessibility, Miller (1991), Kwan (1999), Kim and Kwan (2001), Scott (2003) and several other research-

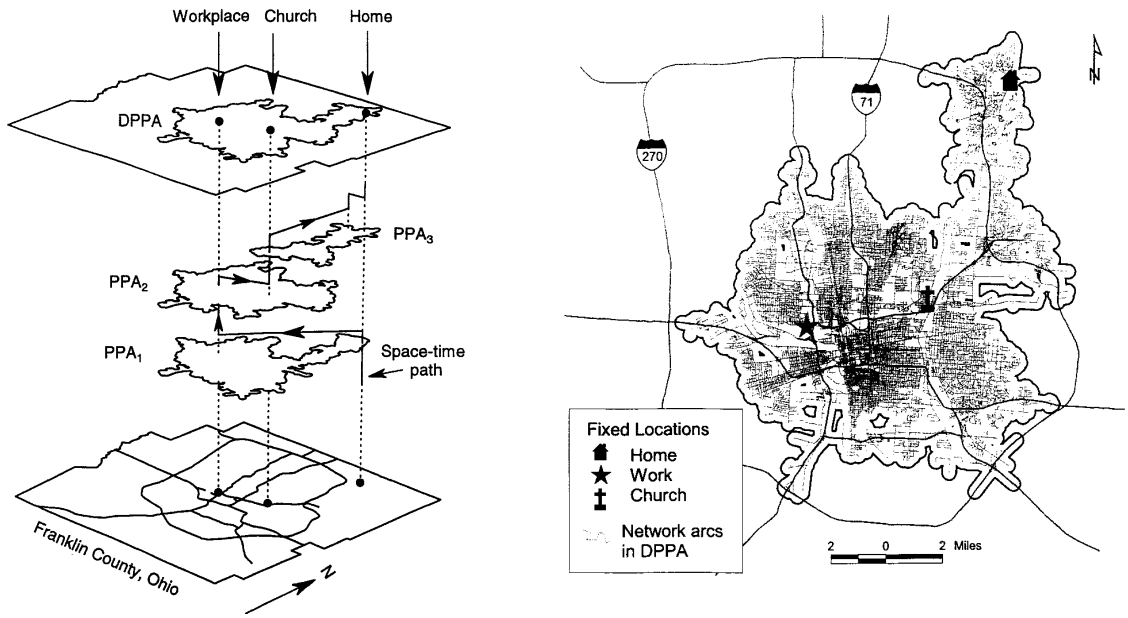
ers develop – mainly GIS – techniques which operationalise space-time prisms for daily travel. The basic idea behind the operationalisation of the so far theoretical Lund school approach is to derive an individual *daily potential path area* (DPPA) which is the physically accessible part of space based one's restrictions, commitments and opportunities (Hägerstrand). The DPPA which is a three-dimensional diagram may then be transformed into a (two-dimensional) map representation which gives the DPPA combined with the available road network and all spatial opportunities within the area of investigation. Compared to conventional accessibility measures space-time measures of individual accessibility have the following advantages:

- Space-time measures evaluate individual accessibility from any place in continuous space rather than considering a single reference point (such as home or workplace) as the focus of daily life. This is based on the notion that a substantial portion of travel consists of multi-stop journeys which implies that various locations become more accessible to places which are visited or passed on the traveller's trip chain or activity programme.
- Second, space-time approaches include personal time-budget and space-time constraints as important determinants of accessibility. These are entirely neglected in the conventional approaches (Kwan, 1999).

The approach was successfully used by Kwan and others to reveal ethnic and in particular gender differences in individual access and it challenged the traditional understanding of accessibility and its calculation. Wu and Miller (2000; 2001; Wu, Miller and Hung, 2001), Pendyala, Yamamoto and Kitamura (2002) and others enhanced the calculation and modelling of space-time prisms by the integration of dynamic flow as well as access utility concepts or the application of stochastic frontier models.

Without doubt, space-time measures of accessibility may be seen as an activity space representation as revealed (often only one or two-day) travel data is used to define individual DPPA. However, only a cross-section of the activity space could be visualised and calculated, as longitudinal data was not available so far.

Figure 11 Daily potential path area (DPPA): Three-dimensional representation and map



Source: Kwan (1999) 214-215

From a more sociological perspective, Scheiner (2001) investigates the distribution of activity locations for a sample of 278 respondents living East and West of the former border in Berlin. The 1998 study, which was part of a comprehensive research programme focusing on transformation processes of the united Berlin, tried to reveal major differences in the daily travel behaviour routines this and the other side of the former Berlin Wall. The respondents were asked to state their main activity locations for shopping, service as well as leisure activities and the frequency of visit. The study yielded interesting results on the integration of East and West Berlin by travellers' everyday use of space: There still exist significant differences between adjacent areas in activity spaces with formers East Berliners orienting towards former East Berlin opportunities and vice versa. However, the study also demonstrated that people tend to choose destinations selectively (e.g. for visiting the doctor) which indicates that still habitual behaviour is still dominating but is challenged by further considerations of spatial choice.

Newsome and her colleagues (Newsome, Walcott and Smith, 1998) used cross-sectional travel diary data from Charlotte to test a method which gives a representation of the maximal area over which travellers could engage in activities. Based on Hägerstrand's space-time theory, they developed an ellipse which should show the observed extent of an activity space. As

foci of the ellipse the home and work location of a traveller was chosen, whereas the location of any combined discretionary activity is estimated as greatest combined distance from those two points. Similar approaches were used to test the impacts of policy measures and telecommunication developments on travel and accessibility (see e.g. Saxena and Mokhtarian, 1997). Even though these studies used revealed travel data, it belongs to the group of approaches which represents potentials of space usage rather than actually observed activity spaces over time.

Based on three-day travel and in-home diary data from Utrecht (The Netherlands) and surrounding areas, Dijst (1999) investigates individual activity spaces and applies a typology of shapes based on different temporal, spatial and spatio-temporal characteristics. These include attributes such as number of visited activity places between departure from a base and arrival at the same or another base and total time spent on activities in the visited activity places (excluding stay time at a base) or area of actual action space and distance between bases and farthest visited activity place. The classification based on about twenty of such attributes finally yielded 17 activity space types which may be summarised as circle, ellipse or line activity spaces – according to the identified shape – and activity spaces of different sizes covering mainly neighbourhoods, the local environment, the region or the whole country. This twofold categorisation was finally linked to socio-economic attributes of the travellers with a strong focus on the implications of part-time and fulltime work for the quality of the activity spaces. It could be generally found that fulltime workers tend to have larger activity spaces than those with part-time jobs.

4 Guiding research principles and questions

This chapter provides the guiding research principles for the following analysis based on what was described as state of the research and what was identified as an analytical shortcoming. The principles essentially capture the aspects *data*, *methodology* and *determinants of travel regularity*. They will be complemented by a set of secondary research questions (hypotheses) which will structure the analysis chapters of this thesis.

(1) Using suitable long-term travel data is the key to reveal temporal and spatial structures of daily travel.

Revealing recurrent structures of daily life travel requires the analysis of longitudinal data sets. Most of the multi-day data sets which have been available till the end of the 1990s are outdated today. Fortunately, a number of long-duration data sets have recently become available, which allow to address issues of temporal and spatial regularity in travel. Due to the availability of exact location data for both, conventional data sets based on travel diaries and – by nature – innovative data sets enhanced by positioning systems, interesting opportunities arise for the analysis of spatial decision making and navigation.

However, using multi-day data requires an appropriate selection, processing and illustration of the information. This will enable the analyst to make best use of the data as input for his/her models of human behaviour as well as the reader/practitioner to comprehend the degree of information involved.

(2) The analysis of urban rhythms *requires the development of (new) conceptual tools and their application.*

The particular character, the richness and the complexity of longitudinal travel data requires the conceptualisation and the application of suitable approaches to represent and explore the inherent intra-personal variability patterns. The earlier investigation of recurrent patterns of travel behaviour shows that there has always been need for a development of new techniques and the adoption of approaches from other fields of research.

(3) The identification of determinants of (a) the level of periodicity in daily travel behaviour and (b) the structure and size of human activity spaces will provide support for planning and policy.

As for other indicators of travel behaviour, the socio-economics of the travellers are believed to play an important role for the rhythms of daily life. For the temporal phenomenon of periodicity, especially the individual commitments and preferences for/of the allocation of time are crucial as determinants. Predominantly, these are the occupation status, fixed commitments and the household structure, i.e. the level of interdependency with other household members. The detailed investigation of such effects is believed to provide interesting findings for the improvement of planning tools/models and the conceptualisation of transport strategies.

Guiding research questions relating to the periodicity of travel behaviour

- The character of the periodicity in daily life travel differs for obligatory, service and leisure-related activities with daily and weekly rhythms. The analysis of several activity purposes will show that the level of flexibility and the possibility of the travellers to re-schedule the activity programmes will have a considerable impact on this character. This leads to the fact that some purposes contribute more to the periodicity of daily life than others.
- For most of the travellers, the periodicity of daily life is dominated by the fixed structure of recurring obligatory activities such as work or education. Less mandatory out-of-home activities such as shopping but especially leisure activities of all kind are often described as temporally and spatially flexible, often spontaneous and difficult to generalise due to the wide range of personal sub-purposes and choice alternatives for location, route, mode and company. A substantial share of the leisure activities belongs to the group of periodic travel patterns, though. Due to the integration of voluntary activities into daily programmes with fixed activities (*activity/trip chaining*), the (growing) societal importance of leisure in general and the embeddedness of leisure activities in coordinated time structures (Shapcott and Steadman, 1978), leisure activities differ from the fixed obligatory activities only in travellers' possibility to reschedule them.
- Travel routines and variability, i.e. the deviation from a form of habitual behaviour, are two complementary aspects of individual travel behaviour (see also Schlich, 2004). This is because
    - the travellers' aspiration for variety-seeking given a highly routinsed and potentially tiring structure of daily life
    - a certain degree of freedom or spontaneity within travel behaviour which leads to punctual rescheduling of temporal arrangements and alterations in original travel decisions in general

  - a dynamic travel environment which forces the traveller to adopt his/her behaviour to permanently changing circumstances such traffic or weather conditions, external decisions by co-travellers or household members etc.

- Travel patterns such as single trips, trip chains or whole day programmes may be described by a more or less detailed list of attributes. Whereas a trip may be defined by its purpose only in a particular analysis setting, it without doubt contains several other attributes such as the departure time, the mode chosen, the amount of people accompanying, parking costs, location of activity at the trip end etc. This fact has certainly implications for the observation of the travel pattern's recurrence and the identification of the similarity of trips or travel patterns. Hence, the periodicity of these patterns very much depend on the level of detail of describing identical patterns, or in other words, on the definition of the recurrence of some event. Finally, it is the strategic decision of the analyst to define the appropriate level of similarity within travel patterns.

Guiding research questions relating to destination choice and human activity spaces

- Few important places dominate the destination choice structure of daily life – this includes especially home and further important locations of regular visits (such as workplace, school).
- However, due to travellers' aspirations and needs to vary locational choice, new yet unknown locations are permanently discovered or added. These "unknown" destinations are predominantly "searched" further away from home then those already visited.
- There exists a constant "innovation rate" in location choice (share of new locations of all locations visited over time) due to variety seeking and externally imposed requirements to visit new locations. The innovation rate is an outcome of personal characteristics (life cycle, occupation etc.).
- The size of (local/regional) activity spaces remains stable over prolonged period of time if the personal situation is unchanged. The size of the activity space is a function of the places known and again, the extent of individual innovation rate.
- The number of individually known places may be approximated by combining findings of
  - total number of places visited over time (reporting period)
  - the individual innovation rate
  - assumptions about the traveller's individual propensities of binding new places
- Due to the economical considerations of the travellers, "activity clustering", i.e. the execution of activities at places nearby is a detectable element of travel behaviour.

– Space matters – not only for travel distances and frequencies but also for the (longitudinal) temporal patterns of travel behaviour. Location within the urban area, accessibility, opening times of potential activity locations widen or narrow the individual time budgets and therefore cause temporal constraints which have effects for the rhythms of daily life. The rhythmic patterns of those spatial attributes force travellers to take these constraints into account and to adopt their own behaviour to them. In other words, activity spaces differ for different local and regional settings.

5 Multi-day data sets employed

This thesis is based on a range of recently collected longitudinal travel data sets which will be presented in this chapter. Before getting into the details of the respective survey designs and the data availability, some remarks are made about the challenges and advantages of using longitudinal (panel) data – in particular when studying timing in transportation and travel behaviour.

5.1 Characteristics and merits of longitudinal (panel) data

Statistics defines the similarities and but mainly the differences between cross-sectional (regression) data as well as time-series data and longitudinal (panel) data: Table 3 gives a synopsis of the discriminating characteristics of the data categories based on Frees (2004). The two main advantages which are connected with longitudinal data are the possibility to study jointly the *dynamics* of a selected variable, i.e. its change over time, together with common cross-sectional issues (comparison between individuals). Besides, heterogeneity effects, i.e. all omitted and immeasurable variables in people's choice process such as different taste or preferences, routines or socio-economic attributes may be analysed and tested for.

Table 3 Regression, time-series and longitudinal data in comparison

	Time scale	Population	Frequency of measurement	Suitability
Regression data	Point of time	Cross section of subjects	One observation per individual	Cross-sectional aspects
Time-series data	Over time	One subject	Repeated measurements	Dynamics of a single issue
Longitudinal data	Over time	Cross section of subjects	Repeated measurements	Dynamics *as well as* cross-sectional aspects Heterogeneity effects

Adopted from Frees (2004)

Given these benefits, longitudinal data is believed to be an appropriate and effective base to study the stability and variability in travel behaviour. Diggle *et al.* (1994) describe further functional and statistical merits of longitudinal data analysis:

- First, if analysing how individuals' behaviour changes with time based on cross-sectional data there is a certain risk that the parameters which represent the expected change within one individual is estimated wrongly. This is because often effects of unmeasured individual attributes such as personal habits which influence variability persist over time and are not captured comparing a person's response to others with a different value. In longitudinal studies in contrast, each observation of a person can be thought of as serving as its (his or her) own control.

- Second, the usage of longitudinal data offers the possibility to distinguish the degree of variation across time for one person from the variation among people. This is particularly important if the variation is large – which is true for many phenomena in travel behaviour due to differences in travellers' socio-economic backgrounds and tastes.

In transportation and especially in travel behaviour analysis, researchers and planners are often interested in how travellers react to changing travel contexts or environments – irrespective if the external reason for change is strategic, i.e. a planning measure or has a natural background such as a certain weather condition. The objective of interest is twofold: On the one hand, the knowledge about the magnitude or power of the reaction is a crucial prerequisite for the estimation of its impact on the system – on the other hand it is essential to know when the feedback starts.

To be aware of the *timing of change* "contributes to the accuracy of a prediction at a point in the future" (Hensher, 1997, 305). In this context, longitudinal panel data plays an important role if its potential to capture timing, *duration* and *event histories* is explored. There is a wide range of applications of such kind, e.g. in the analysis of delays, accident analysis or – like in this thesis – in temporal aspects of activity participation (Bhat, 2000b).

Miller (1999) finally gives three further important arguments for the collection and analysis of multi-day surveys: First, weekend travel – which has been often neglected entirely in cross-sectional travel surveys due to a predominant interest in commuting – has developed as an important demand factor and has a considerable impact on capacities, congestion and emission levels. Second, a realistic representation of travel behaviour requires the understanding of household interactions over more than one day or two. Inner-household time-use planning and

travel decisions often exceed one day periods and have often implications for the availability of mobility tools ("Person A took the train for his weekend trip because Person B needed the household car for getting child C to an event on Saturday"). And finally, sampling and therefore cost-efficiency could support the decision to implement multi-day surveys as for a given number of travel days fewer households are required for interview.

5.2 Data sets

Table 4 provides an overview over the datasets used in the following analysis – however, in different analytical breadth and depth. These data sets span the range from rural village and small town (Canton Thurgau/Switzerland) to metropolitan environments (Copenhagen, Denmark, or Atlanta, USA). In particular the analysis of human activity spaces will try to trace the possible impacts of these scale differences. A first insight into the differences in the level of mobility is provided by Table 5.

The data sources differ substantially by style of data acquisition, structure and amount of information available. Whereas Uppsala, Mobi*drive* and the two Swiss studies were conducted as PAPI travel diaries, the Borlänge, Copenhagen and Atlanta data were collected by in-vehicle GPS devices. The differences are not only visible in terms of the width and depth of the travel related and socio-economic attributes, but also in terms of the resolution of the geocoding which is an important issue for the analysis of human activity spaces. Besides, the definition of a *unique location* – which is a main methodological issue – needs to differ for the different sources given the different sets of available information and geographical resolutions of trip destination coding. A unique location is here defined as the product of geocode and trip purpose (see also Schönfelder and Axhausen, 2004). As will be mentioned below, the unique locations for GPS data had to be created by clustering stop end positions.

Before turning to the data collection procedures of the various surveys in detail, some remarks about the two survey approaches:

Travel diary surveys

Collecting data on personal mobility by travel diaries is still the state of the art methodology in transportation research and practice (see for details Richardson, Ampt and Meyburg, 1995;

Griffiths, Richardson and Lee-Gosselin, 2000)[9]. Travel diary surveys are used to collect up-to-date data on the socio-economics of the travellers and their trip-making as well as information on choice settings, local opportunities and the timing of activities. Travel diary data allows to analyse travel patterns at the time of collection and is used to develop models of behavioural change.

Most of the existing household travel surveys make use of mail and the telephone to gather daily travel behaviour data of a representative sample of the population. Usually, eligible persons in randomly selected households are provided with survey diaries in which they are asked to give information on all travel or activities conducted during the (in this case: multi-week) survey period. Retrieval of this information is conducted over phone or by the mailing back of the survey forms. Often, reminders (by phone or postcard) are sent out after a time of non-response. In order to ensure accuracy of the data collected, the retrieved information is checked for missing, invalid or inconsistent data. The data collection procedure is usually followed by an intensive review, data storage, tabulation, weighting and – if destination choice is a crucial issue – geocoding. Besides, research relates travel diary information with other relevant data sources such as land use, economic activity, or the patterns of environmental exposure.

Collecting multi-day travel diary data is a great methodological challenge for a research team but also a great burden for the participating households and individuals. Some of the difficulties on the data collection over prolonged periods should be mentioned here:

- *Recruiting biases and self-selection threats*: One of the general biases which may occur when implementing household surveys is the lack of representativeness of the sample – even if plausible quota objectives were set. Missing representativeness is in particular discussed if behaviour is observed over a prolonged period which means a substantial burden for the respondents. The willingness to participate might be low for certain groups of the population (e.g. the more active ones in job or leisure), whereas it might be more interesting for others to participate (e.g. those who are after a possible incentive payment). Screening interviews should be used to obtain a minimal set of information about the refusing households to compare those with the participating households.

[9] The respective methodology applied for the travel diary data sets analysed in this dissertation are described in Axhausen, Zimmermann, Schönfelder, Rindsfüser and Haupt (2002) (Mobi*drive*), Marble, Hanson and Hanson (1972) (Uppsala), Löchl, Schönfelder, Schlich, Buhl, Widmer and Axhausen, 2005 (Thurgau) and Schlich, Kluge, Lehmann and Axhausen (2002) (Leisure Study).

- *Drop outs*: Longitudinal or consecutive-days observations belong to the group of panel surveys which bear the danger of sample unit drop outs due to various reasons. The survey administration needs to ensure that retention remains high for the respondents once recruited. As the examples in this dissertation show (see below), this may be well done by e.g. the extensive information of the respondents about the aim and the requirements of the survey as well as permanent care during the reporting period.
- *Fatigue effects*: A final key issue for the quality of longitudinal surveys is presence or absence of reporting fatigue. If trip rates go down systematically over the course of the survey period, this might have "natural" reasons such as vacations but also lower response quality due to decreasing concentration or greater carelessness of the respondents. Temporal trends can be easily identified by a visual inspection and analysis of the trip rates or adequate modelling of the data (such as for example done in Axhausen, Zimmermann, Schönfelder, Rindsfüser and Haupt, 2002). Again, care and information of the respondents during the survey period is an appropriate means of preventing fatigue effects (see also Axhausen, K.W., M. Löchl, R. Schlich, T. Buhl and P. Widmer (forthcoming)).

GPS observations

The Mobi*drive* experiences in particular have increased researchers' interest in accessing long-term travel data bases which eventually capture even seasonalities in travel demand. One obvious technical possibility is the collection of travel behaviour data by GPS devices in connection with GIS mapping. This innovative data collection methodology is promising especially in the field of route choice analysis where exact choice data over longer periods is quasi non-existent. In travel behaviour research, the methodology has been discussed and tested since mid of the 1990s (see Wolf, Guensler and Bachman, 2001 for an overview of feasibility studies). The existing data collection approaches may be categorised as follows (Lee-Gosselin, 2002; Wolf, 2003):

- *GPS based data collection as enhancement of traditional travel diaries*:

  In most of the feasibility studies, the portable or in-vehicle GPS / GIS device acts as a supplementary means of collecting exact time, location, route choice data. Hence, the technique substitutes the respective parts of the ordinary travel diary survey and reduces the reporting tasks of the survey respondents. The remaining trip related information, such as trip purpose, number of people travelling together or activity expenses are collected separately either by means of ordinary travel diary forms or electronic data collection devices such as Personal Digital Assistants (PDA).
- *Passive monitoring*:

> Within a passive monitoring framework, the travellers are observed automatically without requesting any additional information on their trip making (no driver-device interaction). Most of the studies which use passive monitoring are traffic safety driven. The focus of the analysis here is the style of driving respectively the behavioural reaction of the drivers towards external conditions – the rationale for the drive and the activity related to the movement are of a minor interest.

The usage of *passive monitoring* GPS vehicle data represents an innovative approach to broaden the analytical base in ABA. The fully automatically collected data of the respective studies contains movement information for single travellers for up to more than two years (e.g. Atlanta study).

All three data sets used in this thesis are passive monitoring data sets and stem from instrumented vehicle set ups. The technical approach is mainly the combination of mobile GPS data loggers and a Geographical Information System (GIS) (see Draijer, Kalfs and Perdok, 2000 for an example). Vehicles are equipped with an on-board data collection system consisting of a GPS receiver, a data storage device with a GIS for mapping all movements and a mobile power supply. For each trip, the recruited drivers switch on the system independently which starts data transmission to the computer (storage) in short intervals of e.g. second-by-second. After data collection (i.e. the tracking of the travellers), the highly-exact spatial and temporal information is transferred to a conventional PC for processing.

It should be noted that the motivation of the studies arose from different concerns (traffic safety: Borlänge; road pricing experiments: Copenhagen, Atlanta) which causes problems for data analysis and comparability. This includes, for example, the insufficient identification of the driver, their incomplete socio-economic description or the lacking trip and activity purpose information.

Given the incomplete availability and the still preliminary status of post-processing for the three GPS data sets, the analysis provided in this thesis is based on sub-samples of the Borlänge, Atlanta and Copenhagen data. The size and structure of the sub-samples is clarified in the corresponding sections below.

Table 4 Overview over the data sources[10] [11]

Name of the survey	Year	Original focus	Location(s)	Period	Resolution: geocoding	Resolution: purposes	Persons	Trips
Uppsala diary	1971	Travel behaviour	Uppsala, Sweden	35 days	Building	All purposes	144	23’000
Mobi*drive* diary	1999	Stability of temporal patterns	Karlsruhe and Halle, Germany	42 days	Street block	All purposes	361	52’000
Borlänge (ISA Rättfart GPS observation)	2000-2002	Speeding behaviour	Borlänge, Sweden	Up to 80 weeks	Trip ends: GPS; unique locations: Pre-defined clusters of stop ends	Unknown, potentially all	189 veh.[12]	240’000 car trips
Leisure study (SVI Leisure diary)	2002	Leisure travel behaviour and activities	Zürich, Switzerland	84 days	Post code level	31 leisure purposes	75	9’900 leisure activities
Thurgau (SVI Stabilität) diary	2003	Stability of temporal patterns	Frauenfeld and villages in the canton Thurgau, Switzerland	42 days	Building	All purposes	230	37’000

[10] In the following, the data sets are simply titled Mobi*drive*, Thurgau, Uppsala, Borlänge, Copenhagen and Atlanta for better readability.

[11] For those researchers interested in getting access to the data in order to run their own analyses, Appendix A5 provides the relevant web links and contact address.

[12] Private cars only

cont.

Copenhagen (AKTA GPS observation)	2001-2003	Route choice under road pricing	Copenhagen, Denmark	18-24 weeks	Trip ends: GPS; unique locations: Pre-defined clusters of stop ends	Unknown, potentially all	500 veh.	250’000 car trips
Atlanta (Commute Atlanta Instrumented Vehicle GPS observation)	2004-2006	Travel behaviour; test of policy measures such as pricing	Atlanta, USA	Up to two years	Trip ends: GPS; unique locations: Pre-defined clusters of stop ends	Unknown, potentially all	Appr. 500 veh.	Appr. 1’000’000 car trips

Table 5 Selected comparative characteristics of the data sets (mobile days; GPS: after "cleaning")

	Mobi*drive* main study	Thurgau*	Uppsala	Zürich 12-weeks leisure**	Borlänge GPS***	Copen-hagen GPS****	Commute Atlanta GPS
N respondents (GPS: cars with a positive number of trips)	317	230	144	71	66	200	418
Male (GPS: main user)	158	117	63	34	25	140	175
Fulltime (GPS: main user)	120	143	75	37	21	***** 200	225
Mean daily trip rate of mobiles (Std.)	3.9 (2)	4.3 (2.3)	4.5 (2.5)	1.6 0.9	3.8 (1.0)	4.2 (1.2)	4.1 (1.5)
Mean daily distance of mobiles (Std.)	31 (58)	47 (63)	20 (5)	N/A	20 (7)	34 (13)	49 (24)
Mean daily trip duration of mobiles (Std.)	77 (62)	111 (211)	68 (65)	N/A.	27 (8)	54 (17)	74 (72)

*: includes few long-distance/long-duration trips; ** leisure activities only;
*** socio-economic data incomplete for Borlänge; **** control period only;
+ commuters

Data usage strategy

As already pointed out, the data sets will not be analysed in equal level of detail. They are rather used according to their particular features and qualities. In principle, the first strand of analysis (*periodicity of activities*) is based on the travel diary data of the Mobi*drive* and the Thurgau surveys. They offer a rich description of the respondents' socio-economics, a detailed activity purpose categorisation and comparable data structures. The analysis of destination choice as well as activity spaces relies on a wider range of data sets and makes use of the GPS data which are much less detailed in their socio-economic attributes.

Table 6 Data sets: particular features and advantages

Data set	Features
Mobi*drive*	Rich description of personal and household characteristics
	Detailed activity purpose categorisation
Thurgau	Rich description of personal and household characteristics
	Detailed activity purpose categorisation
	"Rural lifestyles": comparability with urban background of Mobi*drive*
	Destination choice: Indication of past visits
Uppsala	Historical comparison with Mobi*drive*
	Rich description of personal and household characteristics
	Detailed activity purpose categorisation
Leisure study	Long reporting period
	Detailed description of leisure activities
	Destination choice: Indication of past visits
Borlänge	Extremely long monitoring period: Seasonalities
Copenhagen	Long monitoring period
	Effects of pricing (excursus)
Atlanta	Extremely long monitoring period: Seasonalities

Table 7 Data usage and analysis concept

	Mobi-*drive*	Thurgau	Uppsala	Leisure study	Borlänge GPS	Copen-hagen GPS	Atlanta GPS
Temporal regularities/rhythms (all subcategories)							
Descriptive	x	x					
Hazard models							
Non-parametric	x	x					
Semi-parametric (Han and Hausman)	x	x					
Fully parametric (Weibull)	x	x					
Destination choice/activity spaces (all subcategories or only partial)							
Enumeration and listing of places visited	x	x	x	x	x	x	x
Responses to planning measures (excursus)						x	
Continuous space representation and measurement							
Confidence ellipses	x	x	x		x	x	
Kernel densities	x	x	x		x	x	
Shortest path networks	x				x		
Activity spaces and socio-economic attributes	x	x	x		x	x	(X)*

* Atlanta where available

5.2.2 Uppsala travel diary data (Uppsala Household Travel Survey)

The Uppsala Household Travel Survey (Marble, Hanson and Hanson, 1972) covers a period of five continuous weeks. The survey was conducted in 1971 and is the basis of a series of publications by Hanson and collaborators concerning the stability of travel behaviour.

The city of Uppsala is located approximately 70 km northwest of Stockholm and had a population of about 130.000 at the time. A random sample of 20 percent of the total population was drawn. The persons who agreed to participate were divided into five waves of equal proportion of six different life cycle groups. The respondents began on five sequential days to fill in the diary. The final sample size was 278 households with 488 persons of which 92 households (respectively 144 persons) were chosen for further analysis by Susan Hanson and colleagues[13]. This group was representative for Uppsala's population. A detailed description of the sampling procedure and the survey instruments is given in Marble, Hanson and Hanson (1972). As part of the survey design, the interviewed persons were contacted frequently. Due to this, the number of participants who dropped out of the survey was below 15%. No signs of significant fatigue effects could be detected (Burnett and Hanson, 1982).

The manual geocoding of the trip destinations for the available sample of 144 persons was successful for 17.138 of the 17.147 trips reported.

5.2.3 Mobi*drive* travel diary data – Dynamik und Routinen im Verkehrsverhalten

The 1999-2001 Mobi*drive* research project proved – in line with the prior survey example from Uppsala – that the fear to lose information in multi-week travel diary surveys was unjustified (see Axhausen, Zimmermann, Schönfelder, Rindsfüser and Haupt, 2002). The implementation of a continuous six-week travel diary was the core of the project.

The travel diary survey itself was conducted in the German cities of Halle/Saale and Karlsruhe in autumn 1999. A total of 317 persons over 6 years in 139 households participated in the main phase of the survey, after testing the survey instruments in a pre-test with a smaller sample in spring 1999 (44 persons)[14]. The PAPI travel-diary instrument was supplemented by further survey elements covering the socio-demographic characteristics of the

[13] This subsample is used in this analysis as well.

[14] The analyses of this thesis are based on the main study data only.

households and their members, the details of the households' car fleet and transit season tickets owned and personal values as wells as attitudes towards the different modes of transport.

One objective of the Mobi*drive* consortium was to provide exact locational data in order to facilitate the analysis of the variability in spatial behaviour over time (e.g. destination-, route- and mode-choice). The precise locational data was obtained by geocoding the trip destination addresses of all main study trips (approximately 40.000 trips). The addresses – including home and workplace locations – were transformed into Gauss-Krüger coordinates in (World Geodetic System (WGS 84) geodetic reference system. The geocoding was positive for about 95% of the reported trips. Due to incomplete addresses and limited availability of digital address information outside the urban cores of the case study regions, the geocodes of the addresses have different degrees of resolution for the different spatial units. For the municipalities City of Karlsruhe and City of Halle, the street addresses could be geocoded on the basis of (small) building blocks (i.e. more than 90% of all geocoded trips), whereas outside the urban boundaries the addresses are available as geocodes of the centroids of the municipality, only.

5.2.4 12 week leisure study (SVI Freizeitverkehr)

The Swiss SVI Freizeitverkehr project aimed to collect long-duration travel data especially on leisure activities (Schlich, Kluge, Lehmann and Axhausen, 2002; Schlich, Simma, Rüssli and Axhausen, 2002). The 12-week travel diary survey which was in the centre of the study was conducted in Zürich/Switzerland (City of Zürich and two smaller suburbs) beginning of 2002. The sample size reached 71 respondents who did not show any significant fatigue effects in reporting. A pre-test in autumn 2001 with 16 respondents helped to finalise the structure of the main study survey.

The survey instrument had its focus on leisure travel requesting respondents' information about start and end times of each out-of-home leisure activity, detailed purpose, mode of travel, place, travel company, expenses and the frequency of recent visits. Besides, a simple time budget survey (by one hour resolution) was added to place the leisure activities into context. The usual socio-economic data was collected to frame the travel diary data.

A total of 5'600 separate leisure activities could be collected. The geocoding was limited to postcode level only. The very detailed coding of the leisure purposes balances this aggregation only to a limited extent. Due to the special focus on leisure travel only and its limited geocoding, the data is not analysed as intensely as the other data sets in this paper.

One interesting and new feature of the survey design was a question in the trip diary instrument whether the trip destination belongs to the set of regularly or at least sometimes visited places or if the destination is entirely new to the respondent. The item yields interesting insights into the characteristics of variety seeking in location choice (see Chapter 7). The same information is available for the Thurgau travel diary data, too.

5.2.5 2003 Thurgau travel diary data (SVI Untersuchung der Stabilität des Verkehrsverhaltens study)

The Thurgau travel diary survey (Buhl and Widmer, 2004; Löchl, Schönfelder, Schlich, Buhl, Widmer and Axhausen, 2005) is a very recent Swiss attempt to 1) collect up-to-date panel data analogous to Mobi*drive* and 2) to develop approaches to explore the stability of travel over the course of one day, within the households and groups of travellers as well as of the mode choice. The survey was performed in the canton of Thurgau (Eastern Switzerland) in 2003 and covers a six week reporting period with a sample of 99 households (230 persons). The majority of destination addresses and household locations could be geocoded with high precision (Machguth and Löchl, 2004). 36'454 of the 36'783 available trips could be geocoded.

5.2.6 Borlänge GPS data (ISA Rätt Fart study)

The GPS data set *Rätt Fart* was made available for travel behaviour analysis by transport psychologists from the universities of Dalarna and Uppsala (Sweden) in 2002. The traffic safety project *Rätt Fart* (Right Speed)[15], based in the Middle-Swedish town of Borlänge, was one of the sub-projects of the Swedish National Road Administration initiative approach *Intelligent Speed Adaptation* (ISA) (see Vägverket, 2000). Rätt Fart in Borlänge itself had its focus on provision of information for the drivers using GPS devices. The study was conducted from 1999 to 2001 with about 260 private and commercial cars which were equipped with GPS and speed adaptation systems over the period of up to 2 years. The essential characteristics speed, acceleration, actual time, location etc. were stored internally for analysis in logs every second respectively every tenth second depending to the road link.

The original movement file contains 245.000 private car trips. The area for detailed monitoring was limited, though, to the town of Borlänge plus some surrounding region – an area with

[15] See http://www.vv.se/isa

a radius of about 20 km around the town centre of Borlänge. Travel out of this boundary was not or only erroneously monitored.

The sub-sample used in this work consists of approximately 52.000 car trips made by 66 vehicles. The period of monitoring covers 27 to 469 reported days and 70 to 2207 reported trips. The available survey period was 29 September 2000 to 4 March 2002. There is only a very limited range of socio-economic variables available for the test drivers.

5.2.7 Copenhagen GPS data (AKTA Copenhagen study)

The AKTA study implemented by the Centre of Traffic and Transport of the Danish Technical University (Nielsen and Jovicic, 2003; Nielsen, 2004) is part of the EU funded project Pricing ROad use for Greater Responsibility, Efficiency and Sustainability in cities (PROGRESS)[16]. AKTA is a real life experiment of road pricing in the greater Copenhagen region.

In 2002 Copenhagen had 620.000 inhabitants in the municipality itself, about 1.800.000 in Greater Copenhagen (Koebenhavn kommun) and more than three million inhabitants in the Öresund region covering Greater Copenhagen and the neighbouring Swedish city region of Malmö.

Approximately 400 cars were equipped with a GPS-based device in three experimental rounds during a period of about two times 8-12 weeks in 2001/2002. Vehicle movement data was collected each second. An onboard system simulated road pricing by providing cost information for every trip within the City of Copenhagen, which was virtually divided by cordon rings defining prizing zones. After two monitoring periods which differed by the pricing scheme virtually applied (high kilometrage, low kilometrage or cordon), the AKTA test drivers were paid an amount of money according to their observed route choice behaviour. The GPS monitoring was accompanied by a telephone based before-and-after survey containing of attitude questions and SP instruments.

The analysis of the destination choice patterns is based on a sub-sample of the total AKTA movement data which consists of 200 vehicles/drivers. The sub-sample contains about 83.000

[16] http://www.progress-project.org/ as of 27.9.2005

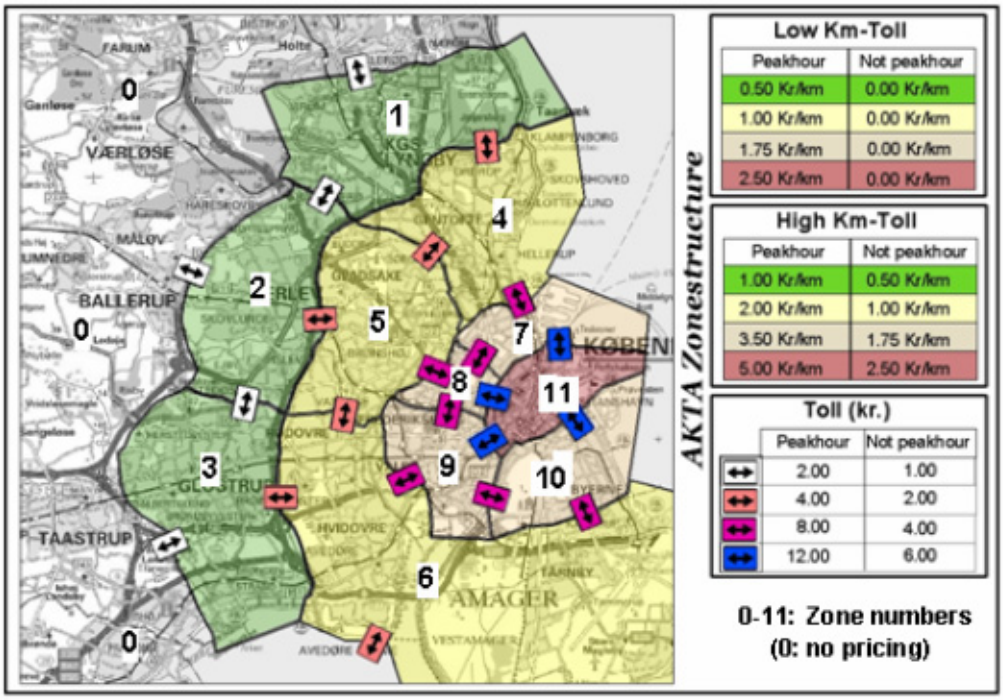
trips (after post-processing) and covers all three combinations of a control period plus a pricing scheme (high and low kilometrage as well as cordon charging).

The resulting data base includes trips with the following control-pricing combinations:

- Control – High kilometrage charge: 48.000 trips
- Control – Low kilometrage charge: 25.000 trips
- Control – Cordon based charge: 10.000 trips

The sampling within the AKTA study is described in more detail in Nielsen (2004). In brief, the participants were recruited based on a factorial design by income groups, residence and work place location and pricing schemes. All drivers belonged to one-car families which is common in Denmark due to high car taxes. All households were located in the area of the pricing experiment. For all participants there was a requirement to travel daily (regular or even fulltime workers).

Figure 12 Copenhagen AKTA pricing structure and zones



Adopted from Nielsen and Jovicic, 2003, 4

5.2.8 Atlanta GPS data (Commute Atlanta Instrumented Vehicle study)

The Commute Atlanta program is funded by the Federal Highway Administration (FHWA) Office of Value Pricing Programs and the Georgia Department of Transportation (GDOT). The main objective of the multi-year Commute Atlanta program is to assess the effects of converting automotive fuel tax, registration fee, and insurance costs into variable driving costs. The project – run by Randall Guensler and his colleagues of the Transportation Group of GeorgiaTech – includes the parallel collection of instrumented vehicle data, household socio-demographic surveys, annual two-day travel diaries, and employer commute options surveys.

The research program spans three phases and includes multiple data collection efforts. The first phase included one continuous year of data collection with no treatments to define baseline travel patterns. Due to seasonal variations in travel, researchers desired a full one-year baseline to develop appropriate relationships between pricing treatments and changes in travel behaviour in future years. The second research phase began in July 2005 and is designed to evaluate the effects of fixed cent/mile pricing. The third phase of research begins in 2006 and includes a real-time congestion pricing increment of 20 cents/mile when the vehicle is operated on the freeway under congested conditions (in-vehicle data terminals display real-time price). Households begin with larger incentive accounts, which are drawn down at a faster rate. The third phase is designed to examine the impact of such financial incentives on travel time choice.

To establish baseline travel patterns, the research team installed 487 GeorgiaTech Trip Data Collectors in the vehicles of 268 participating households to collect second-by-second vehicle activity data (vehicle speed, acceleration, position, and engine operating parameters). Monitoring began for most almost all vehicles in September-December 2003. The data used in preparing the analyses reported here were collected from January-December 2004.

The random stratified sampling framework for household and vehicle recruitment was designed to accommodate hypothesis testing within the incentive-based research goals. Random sampling across the region was desired, given the differences in lifestyles, access to freeways and transit, and land use characteristics. Consumer response to pricing was foreseen to be dependent upon household income as well as ability to respond to pricing incentives, with household structure and vehicle availability being the variables likely to affect the potential for car and ride sharing (see Ogle, Guensler and Elango, forthcoming, for specific recruitment) criteria and opt-in, opt-out analyses).

Due to equipment defect rates which run approximately 3-5%/year (random memory card, GPS, antenna, or other failures), not every vehicle could be monitored on every day in 2004. The sale and purchase of vehicles and household turnover also lead to unmonitored travel. However, the research design and equipment reporting routines allow researchers to determine on which vehicle-days travel is not electronically monitored. The origin and destination location (latitude/longitude) of each trip was recorded and used to examine travel patterns, distances, and ranges of operation for each vehicle. Because each vehicle is tied to a specific household, each trip can be linked to its demographic characteristics. Plus, home and work locations are known for each participant. Because approximately 80% of these vehicles are not shared, the majority of the trips can be linked directly to the age and gender of the driver.

The resulting data base for analysis (after post processing; see below) contains trips of 418 cars owned by 263 households with 655 household members (including non-drivers, children etc.) The number of monitored days per vehicle and mobile days ranges 7 to 367 and 7 to 361 respectively. The average share of usage is about 75%, i.e. the vehicles were used on 75% of the monitoring days on average. Up to more than 3.600 trips per car were observed.

The used sub-sample matches available cross-sectional information – but not in total congruity. This is not illogical considering the unique longitudinal structure of the Commute Atlanta data, the limitations given by the sample size as well as structure and the rough post-processing of the data base. The average number of car trips per day (4.1) is about 20% higher than the NHTS average (3.4), with the mean daily trip duration (70 min/day) and distance (48 km/day) smaller than the national mean (88.7 and 52.8 respectively). Considerably shorter drives were monitored as a result. Similar results were found in earlier comparisons of GPS studies with ordinary cross-sectional travel diary data (Wolf, Schönfelder, Samaga, Oliveira and Axhausen, 2004).

5.3 Cleaning and imputing the GPS data sets (Borlänge, Copenhagen and Atlanta)

As the GPS data collection methodology differs greatly from ordinary travel diary approaches, the vehicle movement information needed to be cleaned and enriched to obtain better comprehensiveness and quality. This cleaning and enriching process will be described briefly in the following:

Because only vehicle activity is monitored, there is a systematic omission of other travel modes such as walking, bicycling, and transit use. Positive driver identification is also not

provided by the system, which appears to increase significantly weekend travel for shared vehicles (see for comparison Guensler, Ogle and Li, 2006). However, the most important element that is not directly collected for each trip is trip purpose. While approximately 60-70% of travel is fairly routine and trip purpose can be identified based upon physical location (home, work, school, day care, and basic shopping), significant additional data processing and imputation will be required (geo-referencing of routine locations based upon travel diary data). However, given that the objective of this analysis is to demonstrate how the data can be used and the ad-hoc analysis of location choice structures over time, the data have been not processed to code trip purposes as has been done in other studies (Schönfelder and Samaga, 2003 and Wolf *et al.*, 2004)[17]. This coding work is ongoing in all three projects. To match minimal needs for a straightforward investigation, the post-processing included initial filtering of the raw data as well as the identification of trip end positions.

Initial filtering and cleaning

The GPS data were pre-processed to remove vehicle activity that does not contribute to travel demand. Vehicle engines are often started and then stopped and then restarted before a real trip begins (perhaps to go back into the residence for a forgotten item). Vehicles are moved in and out of driveways, and are often idled for extended periods. While such information is useful in vehicle emissions analysis, these activities do not constitute vehicle trips. Criteria established in previous studies (Wolf, 2000; Pearson, 2001; Wolf *et al.*, 2001) were applied here. To remain consistent with previous studies, trips with engine operating durations of less than 30 seconds or activity durations of less than 3 minutes were screened from the travel data[18]. In addition, trips for which GPS data were not available (or where a previous trip's destination did not match the next trip's origin location) due to satellite data drops were eliminated. The filtering of the database applying a threshold approach does not systematically prevent that all erroneous trips are detected and erased. Especially if dealing with large data sets such as all used data sets here, it rather guarantees a minimum of quality (see also discussion below).

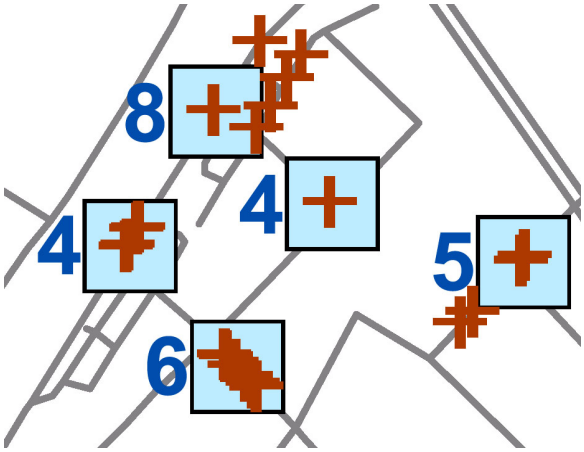
[17] Implemented for the Borlänge data

[18] More recent analysis of the Commute Atlanta data indicates that these criteria are probably a bit too stringent. Drop-off trips to video stores, stops at automatic teller machines, and passenger drop-offs are often of much shorter activity duration. The Atlanta research team is currently analyzing short duration trips to enhance screening criteria and methods.

Identification of trip end position

All three studies establish trip starts and ends through engine operation. Trip recording begins at engine on and stops at engine off[19]. For repeated trips to the same location, the final resting position of the vehicle can vary significantly. Parking location depends upon parking availability. To identify and categorise unique destinations, a straightforward statistical clustering approach was applied. All stop positions within a radius of 200 meters were grouped to one unique location using the highly efficient *nearest centroid sorting* cluster method (Anderberg, 1973). In principle, all stop ends within the given radius were assigned to a calculated cluster means which obviously reduces the number of locations (Figure 13).

Figure 13 Schematic overview: Clustering of observed trip ends (crosses) to unique activity locations (boxes)



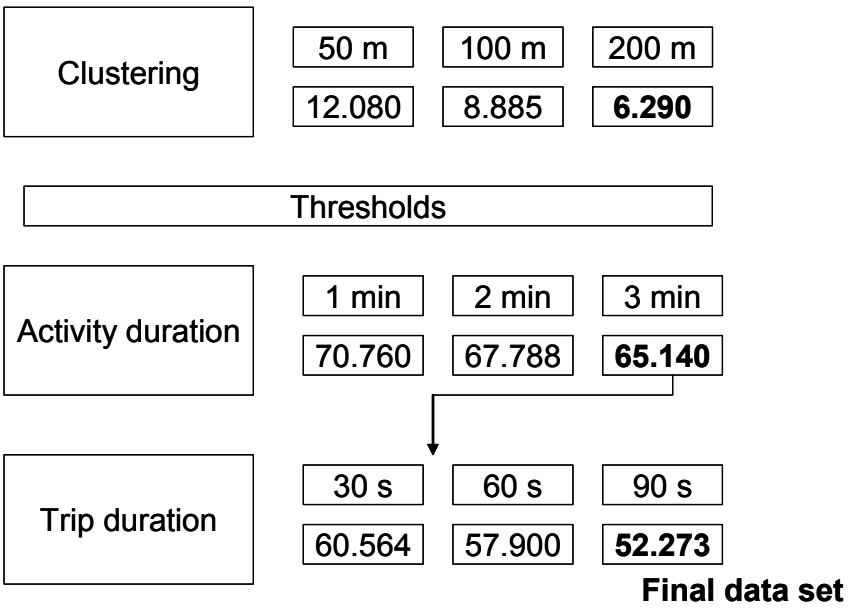
Applying the threshold approach: Implications

Figure 14 exemplarily shows for the Borlänge GPS data how the threshold approach deals with the issue of unique locations and the filtering of potentially irrelevant trips. The size of the chosen cluster radius considerably affects the number of unique locations generated. The

[19] Chained trips that do not include turning the engine off (for example approximately 15% of all trips made during the travel diary comparison period in the Commute Atlanta study) must be identified through post-processing in a GIS system (see Wolf, Oliveira and Thompson, 2003; Ogle, Ko, Li and Guensler, 2006). However, this imputation exercise was not conducted for the data used in this study.

number of total places falls by a half by increasing the radius from 50m to only 200m beeline distance from the cluster seed. This strong elasticity indicates the need for a more sophisticated search strategy. In addition to that, the total number of observed trips is reduced tremendously from about 85.000 to 52.000 trips by applying the threshold cleaning approach (which is independent of the clustering). The final number of trips used for the actual analysis. Again, this shows that more certainty about trip attributes is guaranteed only if a more advanced way of complementing and correcting the GPS traces is applied (such as in Wolf *et al.*, 2004; Chung and Shalaby, 2005; Tsui and Shalaby, 2006).

Figure 14 Exemplary sensitivity analysis for the Borlänge GPS data: Effects of varying clustering and cleaning thresholds for GPS data



6 Modelling the rhythms of activity demand – conceptualisation and analysis

A deeper understanding of the regularity in activity demand is a field of particular interest in travel behaviour research. Moreover, it represents essential background knowledge for private and public decision making in transport. Rhythmic patterns of time use and travel – observed as complete daily trip or activity chains, activity sequences or single main activities – are a constitutive element of our daily lives.

This chapter captures

- the development of a conceptual background for the investigation of the rhythms of activity demand,
- the presentation of suitable tools and modelling approaches to capture the regularity in daily life and
- the analysis of the phenomenon *periodicity* itself.

As many activities and trips occur on a periodic and predictable basis, they might be often explained *historically*, i.e. they are the result of the co-ordination between the human physiology, the dynamic travel environment and the social networks of the travellers (Shapcott and Steadman, 1978).

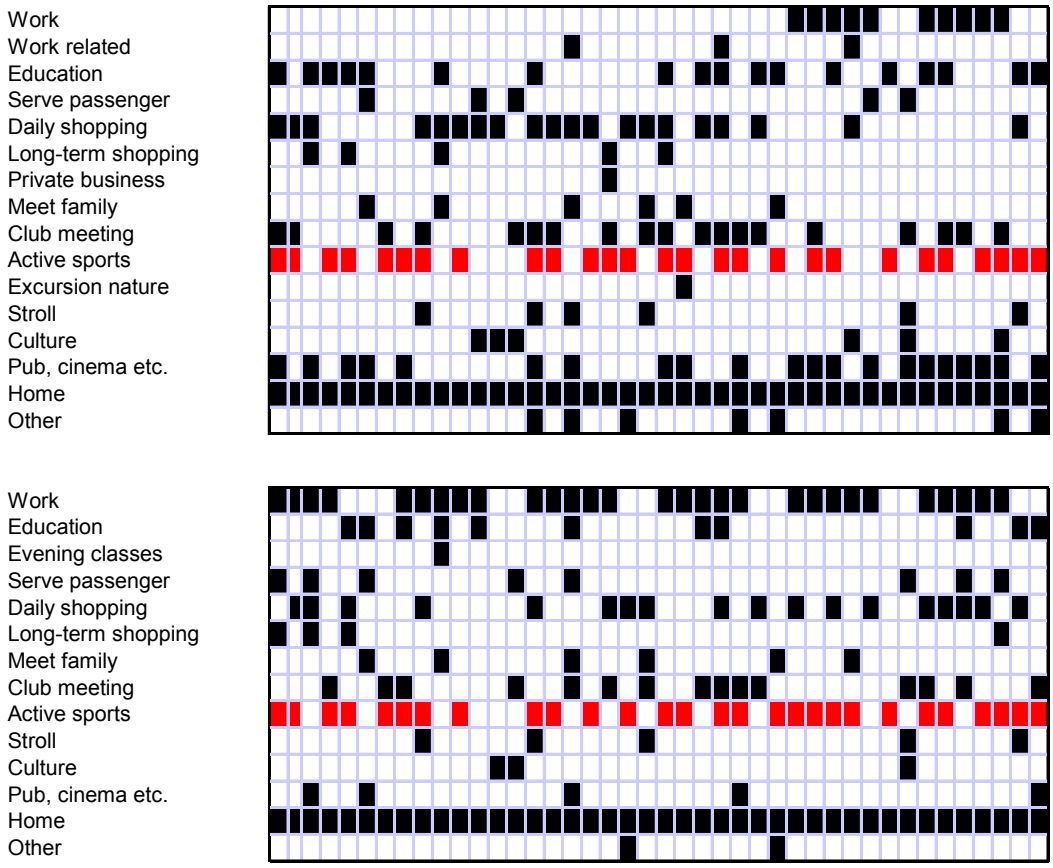
Analysing the character and the determinants of rhythmic patterns in individual travel behaviour requires appropriate methodological approaches. This analysis tries to identify the causal factors of the observed temporal stability and variations using *parametric hazard models*. *Hazard modelling* is used extensively in other fields of technical and social sciences (for an overview see Kalbfleisch and Prentice, 1980). Since the 1990s, hazard modelling has been added to the transport researchers' tool kit of (duration) analysis, too (Hensher and Mannering, 1994). The term *hazard* already refers to the conceptual pillars of the investigation: *probability* or *risk*.

The investigation will stress the importance of the socio-economic background of the traveller by relating his/her personal attributes to the individual – likely regular – structure of activity demand. Two types of hazard models are estimated and tested, which conceptually differ in the level of assumptions made on the temporal development of the probability to start an activity.

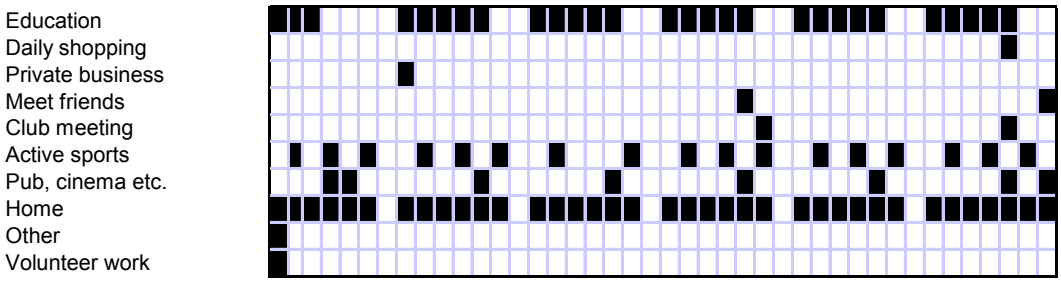
To illustrate the strong regularity in activity demand, Figure 15 presents the activity patterns of three Thurgau survey respondents over the 42 days of reporting. Each of the dark boxes indicates that the respective activity type given on the left was performed at least once that day. The representation shows nicely the patterns of regularity for many obligatory activities but also apparently non-binding activity types such as active sports. However, there is a large amount of sporadic or flexible activity demand for activities with less priority and temporal (spatial) restrictions (e.g. meeting friends). It can be easily seen that there is a lot of joint inner-household activity performance – which remains a challenge for the analysis and modelling of individual travel behaviour (top: joint activity active sports- red/grey shading) (for an initial analysis of joint trips in Mobi*drive* see Singhi, 2001).

Figure 15 Example of activity demand over time

2-person-household. Top: Male, 37, housemaker; bottom: female: 35, fulltime working:



Pupil, 17:



Source: Löchl, Schönfelder, Schlich, Buhl, Widmer and Axhausen, 2005

This visually strong regularity is by nature a result of a certain level of detail of the data representation and reduction. The result will be to some extent relativised if trips are classified by

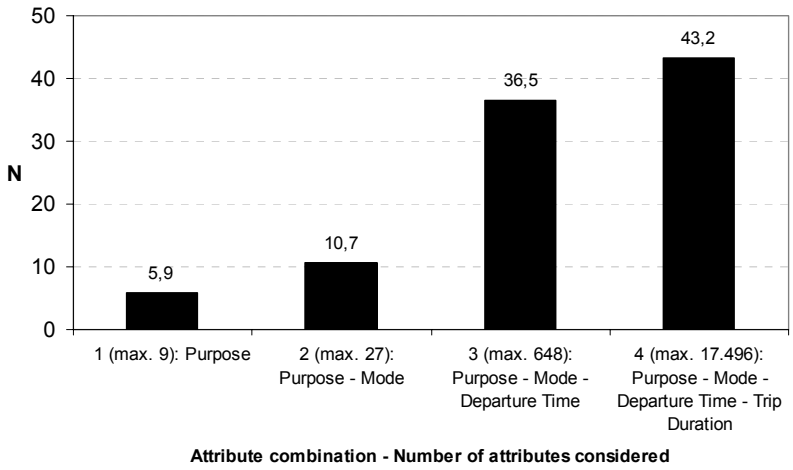
several instead of only one attribute (here: trip purpose). There exists a wide range of possible attributes (Figure 16) which may be taken into account if classifying similar or even identical trips.

Figure 16 Trip attributes: Selected categories

Trip	**Purpose** **Departure time** **Trip duration** **Activity duration** **Location** **Expenditure** **Company** **...**

Figure 17 exemplarily shows the effect of such multi-attribute differentiation of trips. It gives the mean number of observed (identical) trip categories based on a combination of attributes for the Mobi*drive* sample. The results make clear that the level of similarity of trips or activity patterns may vary considerably subject to the researcher's actual characterisation of similarity – which is in fact a triviality, however important if interpreting results on regularity and variability. Whereas similarity based on purpose only is obtained easily, a combination of four attributes might increase the number of different categories of similar trips greatly. This methodological discussion was lead intensively for the development of similarity indices for repetitious travel (Huff and Hanson, 1986; Hanson and Huff, 1988; Pas, 1983; Schlich, 2004).

Figure 17 Level of detail of trip description and mean number of observed identical trip categories: Mobi*drive* sample



Note: Analysis based on nine purposes, three mode categories, departure time categorised by hour and trip duration aggregated to 20 minutes intervals

6.1 An explanatory approach for the regularity in activity demand

The analysis and modelling of the intervals which constitute the rhythms of demand requires a conceptual background which represents both, the process which describes the progression of time between two activities of the same type and the impact of the characteristics of the traveller on this process.

The overall idea of the explanatory approach proposed is *probability* (or *risk*) which is believed to control the execution of a certain activity after a time period of not executing the respective activity (type). The concept therefore not only focuses on duration, but also introduces the term "event" – defined as the start of an activity following an interval. Hence, rhythmic patterns of activity demand may be described as a dynamic relationship between time and events mediated by probability. The degree of the probability itself is shaped by the observed duration process but also by the external travel environment and the attributes of the individual.

The concept of probability for taking a trip is not necessarily new. Campbell (1970) tried to categorise trips to selected destinations – or in other words trips by purpose – by a system of

regular structures constituted by different probability levels. These categories were described as

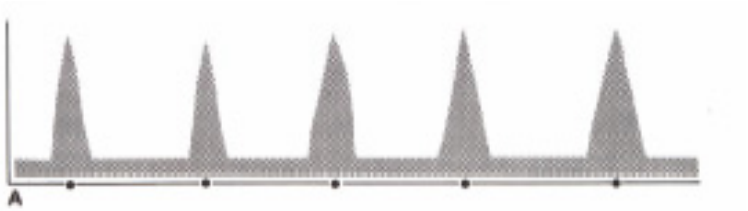
- activities scheduled regularly through time,
- activity demand gradually built-up through time,
- activities evenly spaced in time and
- time-contagious activities.

Figure 18 gives a graphical representation of the classification which was developed based on an intuitive appraisal of daily life rather than on an empirical observation or analysis of longitudinal data. Regular scheduled activities such as club meetings etc. are tied to personal commitments which induce evenly distributed probabilities over time. Activities which are described as regular through time also follow periodic demand – however, they are connected to physiological or other needs which are regular themselves. Travel of this type is for example trips to purchase regularly needed items (e.g. groceries). Time contagious activities "tempt" the individual to execute the same activity again soon after the last time. In other words, the participation in the respective activity increases the probability of (soon) participation – a phenomenon which might for example be the case for "exciting" leisure activities such as playing golf (at least this example is given by the authors of the concept). Finally, some "activities" occur randomly and mostly with a very low probability such as emergencies. In these cases, the probability development may be described as time- as well as traveller independent.

Figure 18 Time and the probabilities of trips to different activity locations

Regularly scheduled activities

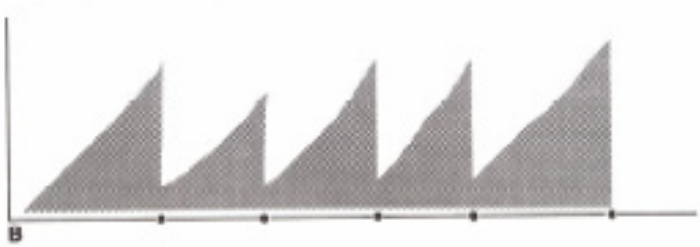
Probability



→ Time

Regular through time

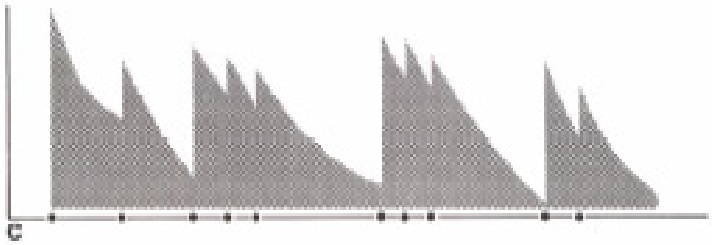
Probability



→ Time

Trips to time-contagious activities

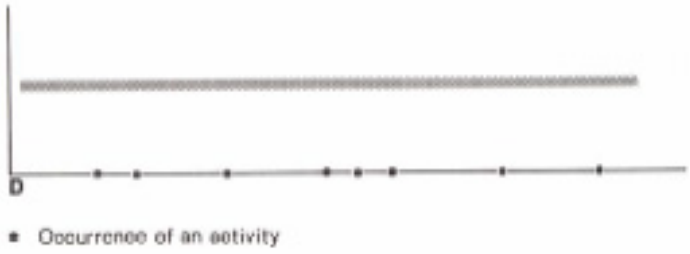
Probability



→ Time

Trips to randomly occurring activities

Probability



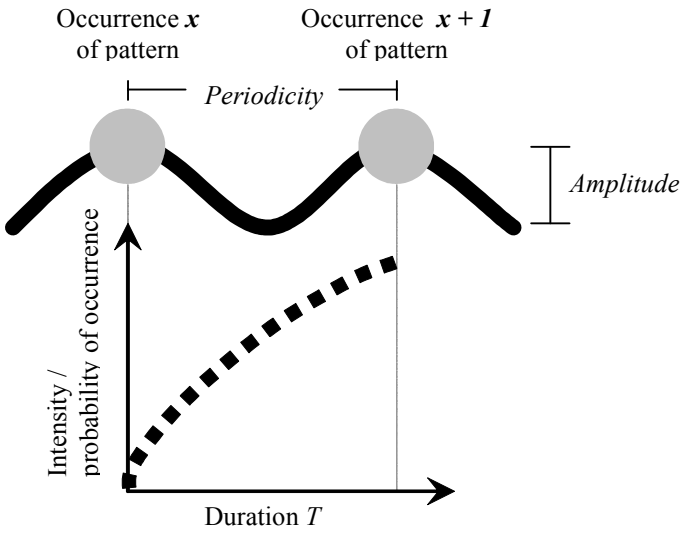
→ Time

Source: Jakle, Brunn and Roseman (1976) 96 after Campbell, 1970

"Increase in demand concept"

Analogous to this early concept, the model (theory) which is the base for the following analysis makes use of the development of probability or risk over time. The approach may be called *increase in demand concept* as it suggests that for most activities there is a natural tendency to build up a demand for executing the same activity again. Figure 19 provides a more technical description of the concept and uses the terminology of *probability/risk* and *event* explicitly: The timing of the occurrence of an identified travel pattern or activity (i.e. the event) at a certain point of time *t* can be expressed as a probability function (dotted line). The probability of occurrence mainly depends on the time elapsed since the last occurrence of the behavioural pattern and will most likely increase over time. Apart from the duration of the observed process personal attributes of the traveller as well as external conditions set by the surrounding travel-environment will have an impact on the development of demand.

Figure 19 Periodicity in travel demand: An explanatory approach



Increase in demand

Source: Schönfelder and Axhausen (2000) 134

Without doubt, this concept includes several theoretical constraints and simplistic behavioural assumptions. Its main drawback is in fact the hypothesis that the assumed increase in probability is a monotone function of time. This implies that individual behaviour is independent of any internal as well as external effects such as the spontaneous modification of one's own activity scheduling or the one of other individuals related with the actor. Besides, it remains questionable if the concept may be assigned to all activity categories in the same way – regardless whether the activity is discretionary or compulsory, constrained by fixed societal structures (e.g. opening hours) or flexible in space and time.

Admitting these restrictions, the proposed approach offers an initial explanatory tool for the explanation of the temporal form of the recurrence of activity performances over time. It allows the comparison of different socio-economic groups by considering different shapes of the probability function for different values for the covariates.

6.2 Some further data considerations

As described in Chapter 3, the durations (spells) between two identical activities constitute the periodicity of activity demand as one of its two main elements. Hence, for this analysis the intervals between identical activities – categorised by purpose – were generated from the Mobi*drive* and Thurgau data sets. The analytical base therefore is duration data which inhabits particular characteristics:

- Empirical duration data as well as possible model estimates are limited to positive values – negative time duration does not exist by definition.
- For various reasons time intervals can be only observed and measured partially – the *censoring problem*. Limited observation periods usually affect the completeness of the measurements, since the relevant processes may have started before the beginning of the investigation or exceed beyond its end. In general, ordinary regression models cannot treat censored durations with values like "at least 5 days".
- In research settings treating aggregate count data such as traffic flows, the application of *Time Series Analysis* has been an effective tool of investigation (see Brockwell and Davis, 1991, for a basic introduction). On the other hand, time series methodology seems to be inappropriate for the activity-based approach with individually assignable attributes of trips and activities. Interval or duration data encompasses some special peculiarities which call for distinctive analysis approaches.

6.3 Analysing duration data: An introduction to Survival Analysis and Hazard Modelling

This sub-section provides an introductory overview of *Survival Analysis* and *Hazard Modelling*. Before turning to specific modelling approaches especially to analyse and predict the impact of individual socio-economic factors on the structure of regularity in travel, some concepts and mathematical basics are given.

In many cases, linear regression modelling is applied to analyse distributions and the correlation of certain determinants with observed values. The application of those models using least-square estimation (LSE) is restricted in the field of duration data due to the model assumptions and the unique character of the empirical data as described above (see Hosmer and Lemeshow, 1999). The constraints led to the development of techniques known as s*urvival analysis* which is used here as the modelling framework for the activity interval data.

The fundamental principle of survival analysis is to specify the occurrence of an event within a certain time span by a probability or risk function called *hazard function* (see Kalbfleisch and Prentice, 1980; Cox, 1984; Kleinbaum, 1986 for basic references). The *hazard function* describes an immediate risk of an event to occur within a time span $t, t+\Delta t$ – provided that the event was not observed by time t. This restriction therefore defines a limited *risk set* which captures events only which have not occurred by $t+\Delta t$ and led to the term *conditional probability*.

Survival analysis techniques are widely used in other research fields and applied settings such as biometry, mechanical engineering or market research. In particular hazard models are employed to forecast the transition from one state to another – e.g. in medicine the event of having a further stroke after a recovery or in engineering the collapse of a device after a period of fault-free performance.

Since the end of the 1980s, hazard models have been estimated in transportation research for a wide range of issues – in the activity-based research for example as a conceptual support of scheduling tools and the analysis of durations of in- and out-of-home activities (Mannering and Hamed, 1990; Hamed and Mannering, 1993; Mannering, Murakami and Kim, 1992; Hamed, Kim and Mannering, 1993; Niemeier and Morita, 1994; Bhat, 1996a; 1996b; Ettema, Borgers and Timmermans, 1995; Reader and McNeill, 1999; Oh, 2000).

Mathematical basics

Survival analysis is a generic term for a group of models which characterise a probability distribution of the random variable T – in other words, the time at which events occur is realised by some random process causing a certain distribution of T. In our model, the event time T defines the end of an interval between two identical patterns of behaviour and thus the starting of the next activity of a same type.

At this time, it seems useful to describe the hazard function and its corresponding functions mathematically, which are the Cumulative Distribution Function *F(t)*, distribution function and survival function as shown in Figure 20.

The *cumulative distribution function F(t)* and its derivative *f(t)* give the probability that an event will occur before or at least at some point in time t.

$$F(t) = \Pr[T < t] \tag{1}$$

$$f(t) = dF(t)/d(t) = -dS(t)/dt = \lim_{dt \to 0} \frac{\Pr(t \le T < t + dt)}{dt} \tag{2}$$

Usually, what is more interesting than the question whether T is less or equal to any value t is surviving a process beyond a certain point – such as the surviving beyond the end of the observation period. The *survival function S(t)* expresses the related probability, i.e. the surviving beyond t. As *S(t)* is a probability, the function is limited to values between 0 and 1 and must be non-negative by definition. Besides, $S(0) = 1$. The function takes diverse shapes according to the character of the processes observed. Along with the restrictions mentioned, it is decreasing in most cases.

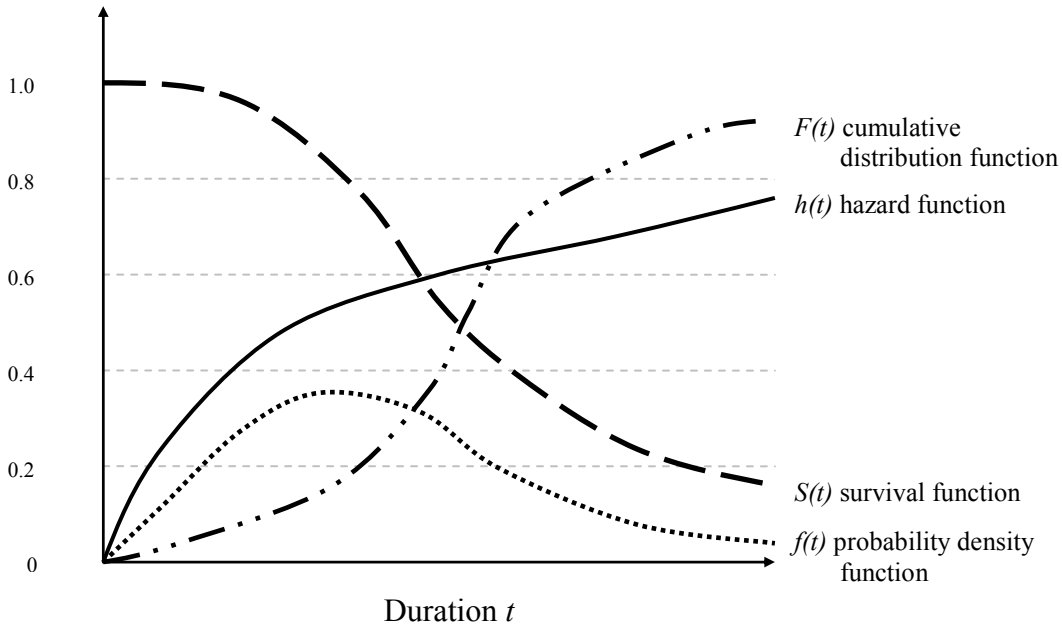
$$S(t) = \Pr[T \ge t] = 1 - F(t) \tag{3}$$

The most common function representing the distribution of durations is the hazard function *h(t)* which is essential for the further modelling process. It gives the probability or the direct risk that the occurrence of an event can be expected in a (small) interval between t and dt - provided that the event has not occurred until this point in time. Thus, only individuals (processes) are considered which belong to the actual risk set, i.e. which survived until the beginning of the mentioned time interval. In contrast to the probability density function – note the similarity of terms – the hazard function represents a conditional density which follows the restrictions of the risk set.

$$h(t) = f(t)/S(t) = \lim_{dt \to \infty} \frac{\Pr(t \le T < t + dt | T \ge t)}{dt} \tag{4}$$

Due to its definition, the interpretation of the hazard rate (as part of the model output) requires some attention. Hazard rates represent latent intensity variables of transition from one state to another rather than common probabilities in a narrower sense (see Schneider, 1991): The higher the value, the quicker the transition from state A to state B takes place on average.

Figure 20 Survival Analysis: Functions



Source: Modified from Hensher and Mannering (1994) 67

6.4 Testing effects by incorporating covariates: Two parametric hazard models

One of the core questions of this work is which determinants other than the observed durations actually have an impact on the periodicity in time-use and travel behaviour. Addressing

this question, two common model approaches will be introduced which are able to incorporate the traveller's attributes to test the probable effects. The approaches belong to the group of so called *parametric hazard models*.

Parametric hazard models

Hazard modelling may not only consider durations as essential determinants for the probability of event occurrence, they are also able to treat duration-independent determinants such as socio-economic attributes or commitments of the travellers. Controlling for these factors yields more realistic model results for the periodicity of travel-behaviour as a result of the above mentioned complex structure of personal and environmental factors. In the following, their impact will be investigated more closely using *parametric hazard models*.

Parametric hazard models treat explanatory variables as a function of a multi-dimensional vector X which has a multiplicative effect on an underlying *baseline* hazard. In non-parametric models without covariate effects it is assumed that potentially explanatory factors equal zero and do not account for any change in probability or risk. Thus, the hazard function given in Equation 6 is a product of two hazard functions – with $h_0(t)$ as a function of survival times whereas $g_0(t)$ gives the potential change caused by subject covariates. In many cases, the term *proportional* hazard is used which describes the fact that the characteristics of the hazard function change according to the values of the covariates. This is at least true given that the ratio of the hazard function remains stable over time (i.e. assumption of constant hazards; $\approx h_1/h_2$). The hazard rate of an individual i is therefore defined as a fixed proportion (*ratio*) of an other individual j with different personal attributes.

$$h(t|X) = h_0(t)g_0(X) = h_0(t)\exp(\beta X) \tag{5}$$

with X = vector of covariates
β = vector of parameters
$h_0(t)$ = baseline hazard without covariate effects

Calculating the logarithm of both sides of the equation, one obtains

$$\log h_i(t) = \alpha(t) + \beta_i x_i + \ldots + \beta_k x_k \tag{6}$$

This equation is important for further distributional baseline assumptions as described later.

The hazard ratio based on the proportionality definition above is given by

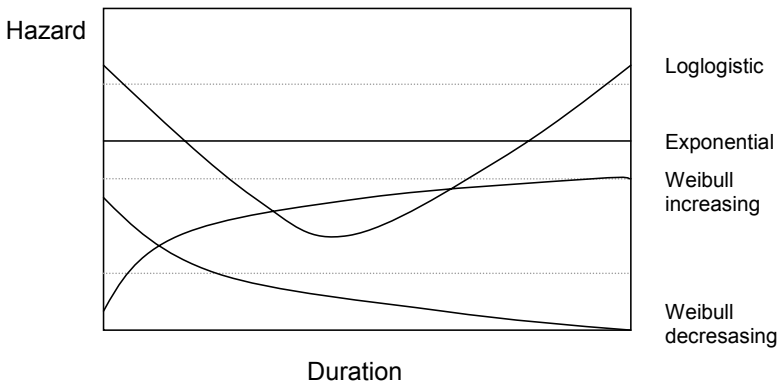
$$\frac{h_i(t)}{h_j(t)} = \left\{\exp \beta_1 (x_{i1} - x_{j1}) + \ldots + \beta_k (x_{ik} - x_{jk})\right\} \tag{7}$$

6.4.2 (Fully) Parametric approach – The *Accelerated Failure Time* (AFT) model

There is a wide range of approaches to parametric hazard models which differ by the distributional assumptions for the baseline hazard. The selection of a certain distribution or the possible omission of an explicit predefinition for a distribution is made following theoretical considerations for the duration process observed.

Fully parametric models are based on both, an explicit distributional assumption for the *baseline hazard* and the incorporation of selected covariates. The shape of the hazard curve is dependent on the distribution assumptions for the processes which control the lengths of the intervals (i.e. the baseline hazard). That is because the hazard function may take several forms (Figure 21), such as monotonously increasing, U-shaped, monotonously decreasing or constant. Monotonously increasing hazard rates (which correspond to a Weibull distribution) are often related to decision processes of which the termination gets more probable with ongoing duration. Processes on the other hand which tend to last longer with ongoing duration create a monotonously falling hazard curve (Weibull distribution, too). A constant shape of the graph (by an exponential distribution) reflects processes with no identifiable relationship between the duration and its ending. Finally, uneven shapes with no distinct direction are possible as well (log-logistic distribution).

Figure 21 Shapes of hazard functions based on different distributional assumptions for the baseline



Source: Modified from Ettema *et al.* (1995) 102

Each of the shown distributions is principally eligible to represent duration processes although wrong assumptions may lead to an incorrect estimation of the baseline hazard (Meyer, 1987). Generally, a theoretical justification of a-priori postulations for the underlying processes is difficult. In some cases it is questionable if the progression of an increase in demand between two identical activity types – as described in Figure 19 – is monotonically rising and therefore of a Weibull type. It is easily possible that the satisfaction of the demand could be meanwhile substituted by other activities or that activities are spontaneously re-scheduled or cancelled at all due to fact that the opportunity to perform disappears.

In this study, the parametric hazard model employed is the *accelerated failure time* (AFT) using the SAS statistical software system. The AFT class of models describes the relationship between the survival function of any two individuals or processes so that

$$S_i(t) = S_j(\phi_{ij} t) \tag{8}$$

with ϕ = constant specific to the pair (i, j).

Linking AFT models to the proportional hazard assumption (Equation 5), they can be defined as

$$S(t|Z) = S_0[t\exp(\beta Z)] \tag{9}$$

with the corresponding hazard function

$$h(t|Z) = h_0[t\exp(\beta Z)]\exp(\beta Z) \tag{10}$$

with Z = vector of covariates.

This analysis will test the Weibull distribution for the fully parametric hazard model. Earlier work recommends the Weibull distribution for the relationship of behaviour and duration (Hamed and Mannering, 1993; Hensher and Mannering, 1994; Bhat, 1996a, b; Oh, 2000). The Weibull model also showed a larger relative reduction in the loglikelihood values compared with other models based on different distributional assumptions (exponential / log-logistic).

Weibull models comprise a simple survival function with

$$S_i(t) = \exp\left[-(t\lambda)^{\gamma}\right] \tag{11}$$

The Weibull distribution is a modification of the exponential with the constant hazard $h(t) = \lambda$ – representing duration independence of event occurrences. The Weibull model itself does not share this restrictive presumption; it rather leads to a monotone character of the hazard with the density function given by

$$f(t) = \lambda\gamma(\lambda t)^{\gamma-1}\exp\left[-(\lambda t)^{\gamma}\right] \tag{12}$$

with γ = Weibull parameter

and the hazard function

$$h(t) = \lambda\gamma(\lambda t)^{\gamma-1} \tag{13}$$

The direction of the monotony is dependent on Weibull parameter with a monotone increasing hazard if $\gamma > 1$ and a monotone decreasing hazard if $\gamma < 1$. The Weibull model is reduced to the exponential form if γ equals 1. Like the Log-Logistic model, it implies restrictive theoretical assumptions due to the monotone character of the hazard (see Hensher and Mannering, 1994 and the later discussion) but eventually allows some duration dependence matching our concept of *increase-in-demand*.

6.4.3 The semi-parametric approaches Han and Hausman approach (ordered logit/probit)

The restrictions imposed by a stringent predefinition of the baseline distribution are bypassed by *semi-parametric hazard models* developed since the 1970s (Prentice, 1976; Cox, 1972; Prentice and Goeckler, 1978; Meyer, 1987). This model type nicely allows to estimate the interactions of covariates in the model without requiring distributional assumptions for the baseline.

As a flexible approach to the semiparametric model family, the model developed by Han and Hausman (1990) is introduced and tested. In contrast to the widely applied Cox approach which uses *partial likelihood* (Cox, 1972; Kleinbaum, 1996 for details of the likelihood estimation), Han and Hausman propose an *ordered response model*. It belongs conceptually to the group of discrete choice models as durations are treated as categorical. The continually measured interval durations t_i (e.g. '26 hours 13 minutes') are transformed into an arbitrarily defined number of categories k with a suitably chosen cell/class size. Each of the cells needs to have at least two observations[20].

Compared to other semi-parametric approaches, the model type has the advantage that it may efficiently handle large number of ties and it circumvents problems with unobserved heterogeneity. Besides, the cell sizes do not have any effects on the covariate parameters which allows to adjust the classification according to the sample size.

Generally, the model is based on the assumption:

$$y = \beta X_i + \varepsilon_i \tag{14}$$

$y_i = 0$ if $y =< i_0$
1 if $i_0 < y =< i_1$
2 if $i_1 < y =< i_2$
J if $y > i_{j-1}$

β_i *parameter estimate*

[20] It is clear that a categorisation of the time scale is a contradiction to the continuous processes which control the interval lengths between identical activities – this discretisation though may be seen as rounding the reported durations. In the particular case of activity demand where most of the activities are performed only once per reporting day, the rounding on the basis of full days (t = 1, 2, 3, …) may be accepted without any significant loss of information.

ε_i *error estimate*

Similar to the fully parametric models shown above, X_i is a multiplicative vector with impact on the hazard rate (e.g. attributes of the traveller or the performed activity)

It should be mentioned that a time-constant character of the variable X is assumed, which means that there is no change of its value over the period of observation. The error estimate ε describes unobserved effects on the interval durations. The semiparametric model uses a logistic or normal distribution of ε.

Han and Hausman start their actual derivation of the model with the *proportional hazard* specification of Prentice (1976):

$$h(t) = \lim_{dt \to \infty} \frac{\Pr(t \le T < t + dt | T \ge t)}{dt} = h_0(t) \exp(\beta_i X) \tag{15}$$

A logarithmic transformation leads to the integrated hazard function:

$$\log \int_0^{T_i} h_0(t) dt = X_i \beta + \varepsilon_i \tag{16}$$

with an *extreme value* distribution for ε_i

$$F(\varepsilon_i) = \exp(-\exp(\varepsilon_i)) \tag{17}$$

In the following, it is defined that

$$\log \int_0^{T} h_0(t) dt = \delta_T \tag{18}$$

With T=1, ..., B

which gives a probability of failure P in the period t for individual i:

$$P[B_{t-1} < T_i < B_i] = \log \int_{\delta_{T-1}}^{\delta_T} {}^{-X_i\beta}_{-X_i\beta} f(\varepsilon) d\varepsilon \tag{19}$$

The logs of the integrated baseline hazards, δ_t, are treated as constants in the different periods are estimated with the (unknown) parameters βi.

The log-likelihood function is found defining an indicator variable y_{it} with the values

$$y_{it} = \begin{cases} 1 \; if \in -1;] \\ 0 \end{cases} \tag{20}$$

$$\log L = \sum_i \sum_T y_{iT} \log \int_{\delta_{T-1}}^{\delta_T} {}^{-X_i\beta}_{-X_i\beta} f(\varepsilon) d\varepsilon \tag{21}$$

The distributional assumptions for the error estimate ε determine the form of the model. A standard normal distribution results in an ordered probit form whereas an extreme value distribution for ε yields an ordered logit form. Only the latter case actually strictly meets the proportional hazard specification of (15). However, as there is great similarity between the distributions (normal and extreme value distributions only differ at the edges of the curve) the ordered probit model remains a useful approximation.

Finally, the hazard rate *h(t)* may be estimated by

$$h(t) = \Pr ob\lfloor t_j < t < t_j + 1 \rfloor / \Pr ob(t \geq t_j) \tag{22}$$

The hazard rate is calculated using the forecast cell probabilities for the model at the means of the different variables. These probabilities are divided by the cell width if values are given to so (Greene, 1998).

6.5 Analysis and results

The respondents in the Mobi*drive* and Thurgau survey were asked to provide the exact activity purpose for all leisure as well as all non-pre-coded activities explicitly. This opens up the opportunity for a fine categorisation of the activity purposes which exceed the usual number of ten or even less. The categorisation was made comparable to the coding applied in the earlier research project City:mobil (Götz, Jahn and Schultz, 1997) which is given in Appendix A1.

The analyses using the presented fully and semi-parametric approaches refer to a selection of activity purposes with a focus on service and leisure. Obligatory activities – in particular work and education – are not considered here as those activities by nature underlie a strong regularity. However, this does not mean that important and interesting investigation in the variability

and stability of compulsory activities can be undertaken. For example, Mahmassani and others (Jou and Mahmassani, 1996; 1997; Bhat, 1996b; 1997; 1999; 2002) did substantial work on the dynamics of departure time choice and trip chaining of commuting trips (see above).

Following activity purposes are covered in the analysis:

- Daily shopping
- Long-term shopping
- Private business
- Club meeting
- Active sports
- Meet family or friends
- Meet friends
- Stroll
- Going out (bar, restaurant, cinema)

Selected important characteristics of the activity performance are displayed in Table 8. As could be expected, there is great variance in the determinants given the fine categorisation of the purposes. This is especially true for the activity durations. From a planning and political point of view, there is a particular interest in the mode choice behaviour for the different types. An efficient supply respectively a demand matching policy is without doubts depending on an analysis and forecast which is based on an activity type-specific differentiation. The traditional differentiation between obligatory (school and work etc.) and voluntary trips (shopping, maintenance and leisure etc.) might be a too simplified aggregation of the human activity system. Even *leisure* as one category covers a wide spectrum of activity types with different regularities, priorities and interconnections with other activities which result in different activity programmes.

In addition to that, the tables present the differences in the travel and activity characteristics between the Thurgau and the Mobi*drive* survey. What become obvious are the differences between the suburban or rural lifestyle in the canton of Thurgau and the urban demand structures for Karlsruhe and Halle. This can be recognised by for example a lower share of car usage over most activity purposes, smaller travel distances due to higher land use densities and generally lower speeds due to the different mode choice structure but mainly due to the urban traffic situation and congestion.

Table 8 Characteristics of selected activity types (unweighted; Mobi*drive*: main study, Thurgau: total sample)

Activity type		N	Share car * [%]	Mean distance (Std.) [km]		Mean trip duration (Std.) [min.]		Mean activity duration (Std.) [min]	
Daily shopping	MD	4085	41	3	(15)	11	(10)	36	(97)
	TH	2033	51	4	(9)	9	(13)	45	(148)
Long-term shopping	MD	1638	54	6	(10)	17	(15)	62	(110)
	TH	993	70	10	(16)	16	(21)	53	(113)
Private business	MD	1335	73	19	(48)	26	(37)	134	(210)
	TH	2024	66	8	(16)	12	(22)	58	(161)
Club meeting	MD	649	37	7	(22)	15	(19)	140	(169)
	TH	845	62	7	(10)	11	(12)	137	(117)
Active sports	MD	1146	58	6	(11)	18	(25)	150	(164)
	TH	1144	50	7	(10)	21	(37)	178	(216)
Meet family / friends	MD	2361	53	16	(49)	24	(37)	265	(475)
	TH	1733	66	16	(33)	17	(66)	202	(251)
Stroll	MD	1592	16	6	(11)	38	(35)	398	(532)
	TH	1189	16	4	(6)	48	(36)	492	(568)
Going out (bar etc.))	MD	1183	46	6	(14)	18	(18)	136	(120)
	TH	1584	44	7	(22)	6	(91)	114	(141)
For comparison:									
Work	MD	4134	49	9	(15)	20	(15)	407	(208)
	TH	3702	62	15	(21)	20	(28)	312	(215)
School / education	MD	2324	13	5	(8)	18	(14)	296	(132)
	TH	4476	34	7	(15)	15	(23)	161	(198)

* Car driver and passenger; MD = Mobi*drive*, TH = Thurgau

A first insight into the long-term structure of demand is provided by the shares of the interval lengths between two activities of the same type. Table 9 shows that many activity types are performed twice or even more times per day (interval length = 0). Besides, there is a strong

indication that especially for some activities such as shopping there is a one- respectively two-day-rhythm with a flexible background pattern, though. A clear weekly rhythm can be identified for leisure activities such as club meeting or active sports. Finally, for a range of other purposes there is no obvious temporal pattern of demand visible.

Table 9 Share of interval lengths between two activities of the same type in days (unweighted; Mobi*drive*: MD, Thurgau: TH) [%]

Activity type		N	**0**	**1**	2	3	4	5	6	**7**	8	9	10	11	12	13	14
Daily shopping	MD	4085	**18**	**30**	16	10	6	3	3	**2**	1	1	1	1	0	0	**0**
	TH	2033	**14**	**26**	16	10	6	4	3	**5**	1	1	0	0	0	0	**1**
Long-term shop.	MD	1635	**15**	**14**	11	7	5	4	4	**5**	2	2	2	1	2	1	**1**
	TH	993	**18**	**10**	8	6	6	5	4	**5**	2	2	2	1	1	1	**1**
Private business	MD	3524	**24**	**25**	11	8	5	4	3	**3**	1	1	1	1	0	1	**1**
	TH	2024	**23**	**20**	11	7	4	3	3	**3**	1	1	1	0	0	1	**1**
Club meeting	MD	643	**6**	**17**	11	8	7	4	2	**15**	1	0	0	1	0	0	**3**
	TH	845	**7**	**15**	13	9	6	6	5	**11**	2	1	1	0	0	0	**2**
Active sports	MD	1146	**6**	**26**	16	7	7	4	2	**9**	2	1	1	0	1	1	**2**
	TH	1144	**9**	**22**	14	10	8	3	3	**9**	1	1	1	1	0	0	**2**
Meet family / fr.	MD	2358	**15**	**26**	12	8	6	5	3	**2**	1	1	1	1	1	1	1
	TH	1733	**15**	**20**	8	7	4	4	4	**3**	2	1	1	1	1	1	**2**
Stroll	MD	1592	**29**	**37**	5	3	2	1	2	**2**	1	0	0	0	1	1	**1**
	TH	1189	**20**	**38**	8	4	4	2	2	**3**	1	1	1	0	1	0	**1**
Going out	MD	1183	**9**	**21**	10	8	5	4	4	**5**	3	2	1	1	1	1	**1**
	TH	1584	**16**	**30**	10	8	4	3	4	**4**	2	1	1	1	1	0	**0**

Note: Longer intervals (>14) and missing values excluded, i.e. sum is not necessarily 100%; MD = Mobi*drive*, TH = Thurgau

6.6 Applying Survival techniques

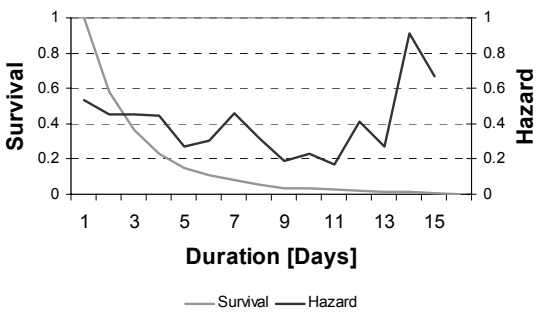
Before turning to the effects of socio-economic attributes of the travellers in detail, the empirical survival and hazard rates of the intervals for the different activity purposes are presented (Figure 22). The figure shows selected rates for Mobi*drive* (Karlsruhe) based on the

life tables method (see e.g. Berkson and Gage, 1950). The method efficiently calculates survival and hazard rates especially for large event time data sets. Life tables – in contrast to the commonly used Kaplan-Meier estimator (Kaplan and Meier, 1958) – group the durations into user-defined intervals. Here, intervals of one day are chosen.

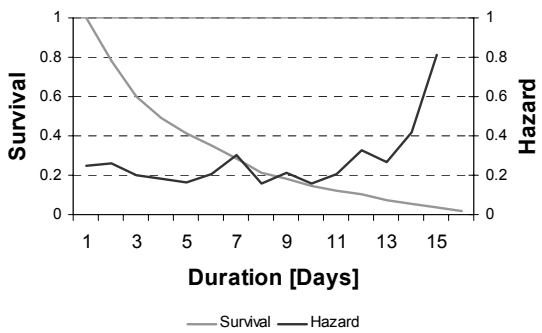
The temporal structure of activity demand becomes clear analogous to Table 9. It is interesting that most of the hazards curves have a local maximum after one and/or two weeks respectively. This is especially obvious for the often structured leisure activities club meeting and active sports. However, this shows only in part that there is a predominant 7-days periodicity for the whole sample as the hazard rate does not consider the total number of observations to a point of time but the risk set only. In principle, the survival rates indicate the real significance of the trend at the respective point of time. For example, the relatively high probabilities for the activities daily and long-term shopping at seven days are true only for few respondents or observations (i.e. survival rate around or below 0.2).

Figure 22 Empirical survival and hazard rates based on life tables: Mobi*drive* – Karlsruhe subsample

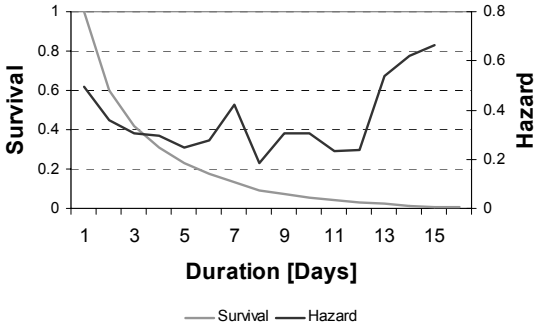
Daily shopping



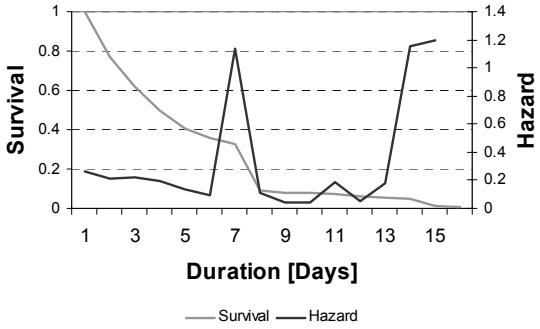
Long-term- shopping



Private business

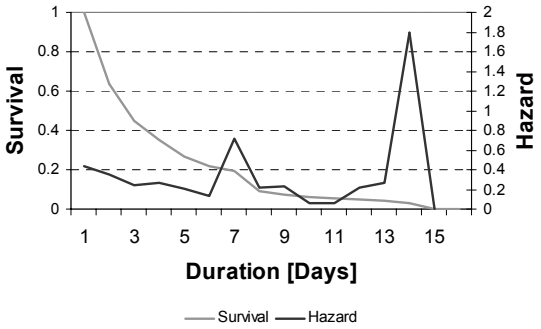


Club meeting

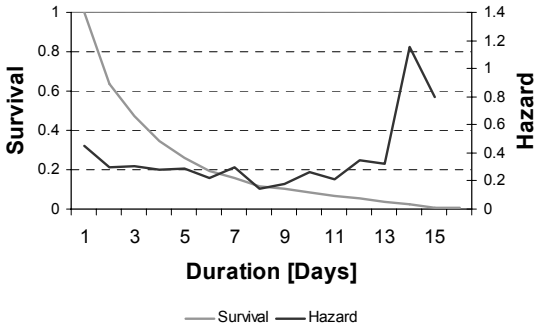


cont.

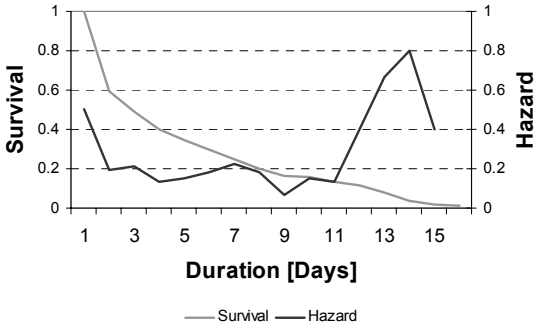
Active sports



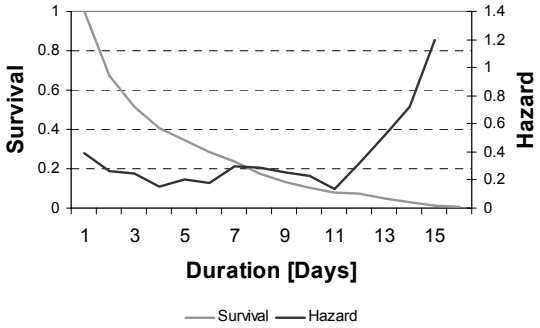
Meeting family or friends



Stroll



Going out (Bar, restaurant, cinema)



Covariates

As explanatory variables for the model estimation, a set of personal and household related characteristics is chosen which represent common determinants of travel and activity demand (Table 10). Per capita income as well as car availability was plausibly imputed were necessary using the modal value of socio-economic group based on household size, number of adults as well as number of vehicles in household.

The model estimation for the Mobi*drive* distinguishes between the two cities Karlsruhe and Halle by incorporating a city dummy. This will take account of the fact that there are differences in the respective travel behaviour (see e.g. Schlich, König and Axhausen, 2000). A similar differentiation is made for the Thurgau data with a dummy for the (small) town of Frauenfeld (canton's capital) in contrast to the surrounding villages.

The (overall) covariate means show the socio-economic parallels and differences between the two samples considered for the following analysis. Differences are obvious for the family structure (married/parent), club membership, occupation status (fulltime working), income structure, car availability/car usage. This is again partly due to the differences in the urban and more rural lifestyles, but more simply due to the socio-economic composition of the respective samples. A harmonisation of this composition towards Mobi*drive* was not part of the Thurgau survey.

Table 10 Selected covariates: Means (Std.)

Covariate	Mobi*drive*	Thurgau
Personal		
Male	0.5 (0.5)	0.5 (0.5)
Age	39 (18)	39 (18)
Age^2	1880 (1476)	1916 (1417)
Is married or lives in fix partnership	0.5 (0.5)	0.6 (0.5)
Is parent	0.4 (0.5)	0.2 (0.4)
Is club member	0.3 (0.4)	0.6 (0.5)
Fulltime working, i.e. working hours > 30 h / week	0.4 (0.5)	0.6 (0.5)
Dog owner (>10% of all trips with dog)	0.1 (0.3)	0.1 (0.3)
Household related		
Number of household members	2.9 (1.2)	3.1 (1.6)
High income: > 2000 DM / 3000 CHF per HH capita	0.3 (0.4)	0.6 (0.5)
Car usage		
Number of cars in household	1.2 (0.6)	2.0 (1.5)
Is main car user: Holds driving license and has permanent access to car	0.4 (0.5)	0.8 (0.4)
Local differentiation		
Lives in Karlsruhe (Mobi*drive*) / Frauenfeld town (Thurgau)	0.5 (0.5)	0.5 (0.5)

Note: Means based on total sample; particular covariate means for single models by activity purpose see estimation results in the respective chapter or in the appendix A6

6.7 Results

The results section gives an overview over the model estimations trying to emphasize the parallels and differences of the model types chosen. A detailed discussion of the implications for methodology development and practice will follow at the end of the chapter and in the conclusions section. The section starts with some notes on the interpretation of the parameter estimates of the particular model approach and provides the actual explanation after that.

Weibull analysis

Since the Weibull parametric model belongs to the group of AFT models as well as to the proportional hazard model class its estimates may be easily translated into relative survival ratios when suitable transformed before.

The following tables give the Weibull model estimation results (Table 11 and Table 12 in detail - Table 13 and Table 14 as overview about the covariate effects). The model estimation was done using the SAS System (Allison, 1995). In general, positive coefficients represent longer survival times for individuals whereas negative coefficients are associated with shorter spells. In other words, the negative sign indicates a higher transition rate between two identical patterns of behaviour. This is because the hazard is given by $\lambda = \exp(-\beta Z_i)$ in fully-parametric approaches. The estimates may be transformed into more informative figures by some simple calculations: the multiplicative effect of the chosen indicator (dummy) covariates may be found by taking e^{β} which yields the estimated risk ratio (RR) of the expected (mean) survival times for the two groups (Allison 1995, p. 65). For example: For the 1 – 0 variable "High income" in the Mobi*drive* "Daily shopping" model we get a risk ratio of 0.88 which means that – controlling for other covariates – the expected time between the two identical activities is 12% lower than for those respondents with lower income. For count variables, an analogous indicator is obtained by $100(e^{\beta}-1)$ which provides the percent increase in the expected survival time for each one-unit increase in the variable.

Table 11 Parameter estimates (β) and effects of covariates: AFT Weibull for Mobi*drive*

Activity type	Daily shopping		Long-term shopping		Private business		Meet family / friends		Club meeting		Active sports		Excur-sion into nature*		Stroll		Going out (bar etc.)	
	β	RR	β	RR	β	RR	β	RR	β	RR	β	RR	β	RR	β	RR	B	RR
Lambda	**0.01**		**0.00**		**0.01**		**0.02**		**0.00**		**0.00**		1.89		**0.02**		**0.02**	
γ	**1.29**		**1.28**		**1.20**		**1.17**		**1.32**		**1.30**		1.59		**1.38**		**1.26**	
Intercept	**4.46**		**5.56**		**4.76**		**3.86**		**6.07**		**5.66**		-0.63		**4.15**		**4.04**	
Personal																		
Sex	0.05	1.05	0.01	1.01	-0.04	0.96	0.06	1.07	0.12	1.13	-0.15	0.86	0.37	1.45	**-0.17**	**0.84**	-0.02	0.98
Age	**-0.01**	**0.99**	**-0.04**	**0.96**	**-0.02**	**0.98**	0.01	1.01	-0.02	0.98	**-0.04**	**0.96**	0.04	1.04	**0.03**	**1.03**	**0.03**	**1.03**
Age^2	**0.00**	**1.00**	**0.00**	**1.00**	0.00	1.00	0.00	1.00	0.00	1.00	**0.00**	**1.00**	0.00	1.00	0.00	1.00	0.00	1.00
Married	-0.02	0.98	0.11	1.12	0.07	1.08	**-0.16**	**0.85**	0.10	1.10	0.04	1.04	0.00	1.00	**-0.22**	**0.81**	**-0.11**	**0.90**
Is parent	**-0.19**	**0.83**	0.16	1.17	**-0.25**	**0.78**	0.12	1.12	**0.77**	**2.17**	**0.47**	**1.60**	-1.03	0.36	**-0.51**	**0.60**	**-0.26**	**0.77**
Club member	0.06	1.07	-0.09	0.92	**0.09**	**1.09**	0.03	1.03	-0.15	0.86	**-0.51**	**0.60**	-0.28	0.75	**0.25**	**1.29**	-0.08	0.92
Dog owner	**-0.15**	**0.86**	-0.01	0.99	**0.22**	**1.24**	0.01	1.01	-0.24	0.79	-0.04	0.96	-0.16	0.85	**-0.95**	**0.39**	0.28	1.33
Fulltime work	**0.36**	**1.43**	**0.23**	**1.26**	**0.12**	**1.13**	0.11	1.11	-0.23	0.80	0.01	1.01	-0.66	0.52	**0.32**	**1.37**	-0.08	0.92
Household																		
N HH members	0.04	1.04	-0.06	0.94	**0.06**	**1.06**	0.04	1.04	**-0.30**	**0.74**	**-0.12**	**0.89**	**1.19**	**3.28**	**0.11**	**1.12**	**0.16**	**1.17**
High income	**-0.13**	**0.88**	-0.03	0.97	**-0.15**	**0.86**	0.06	1.06	0.01	1.01	**0.37**	**1.45**	**1.41**	**4.09**	**-0.61**	**0.54**	-0.02	0.98
Car usage																		
N vehicles	0.05	1.05	**0.12**	**1.13**	-0.01	0.99	0.03	1.03	0.08	1.09	**0.14**	**1.14**	0.16	1.17	-0.08	0.92	0.00	1.00
Main car user	0.02	1.02	0.08	1.08	0.07	1.07	**-0.14**	**0.87**	**-0.24**	**0.78**	**-0.24**	**0.78**	-0.17	0.84	**0.17**	**1.19**	**-0.33**	**0.72**

Area type																		
Karlsruhe	-0.03	0.97	0.02	1.02	-0.07	0.93	0.01	1.01	0.01	1.01	**-0.18**	**0.84**	0.06	1.06	**0.47**	**1.60**	-0.03	0.97
N	3019		1031		2346		1670		447		899		51		883		800	
Loglikelihood (0)	-3862		-1371		-3200		-2326		-588		-1223		-66		-1256		-1089	
Loglikelihood (*β*)	-3764		-1348		-3138		-2270		-568		-1144		-58		-1027		-1054	
-2Chisquare	196		45		124		111		42		158		18		460		71	
Pseudo R^2	0.06		0.04		0.05		0.06		0.09		0.16		0.29		0.41		0.09	

Note: Dependent variable: Interval length in hours; RR: Risk ratio; **Bold**: Covariate significant at 0.05 level

* Model not significant: See small N

Table 12 Parameter estimates (β) and effects of covariates: AFT Weibull for Thurgau

Activity type	Daily shopping		Long-term shopping		Private business		Meet family / friends		Club meeting		Active sports		Excur-sion into nature		Stroll		Going out (bar etc.)	
	β	RR	β	RR	β	RR	β	RR	β	RR	β	RR	β	RR	β	RR	B	RR
Lambda	**0.00**		**0.01**		**0.03**		**0.03**		**0.00**		**0.01**		**0.01**		**0.00**		**0.01**	
γ	**1.33**		**1.40**		**1.23**		**1.19**		**1.41**		**1.31**		**1.11**		**1.40**		**1.24**	
Intercept	**5.34**		**4.53**		**3.52**		**3.61**		**5.36**		**5.06**		**4.62**		**5.79**		**4.52**	
Personal																		
Sex	**0.21**	**1.23**	0.09	1.09	0.08	1.08	**0.12**	**1.12**	0.03	1.03	0.01	1.01	0.05	1.05	-0.02	0.98	**-0.19**	**0.82**
Age	**-0.05**	**0.95**	0.01	1.01	0.02	1.02	**0.04**	**1.04**	**-0.03**	**0.97**	-0.02	0.98	0.01	1.01	-0.01	0.99	-0.02	0.98
Age^2	**0.00**	**1.00**	0.00	1.00	0.00	1.00	**0.00**	**1.00**	**0.00**	**1.00**	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00
Is partner	**0.14**	**1.15**	-0.16	0.85	0.09	1.10	-0.09	0.91	**-0.42**	**0.65**	**0.27**	**1.31**	-0.44	0.64	**-0.25**	**0.78**	**-0.13**	**0.88**
Is parent	-0.12	0.88	**-0.30**	**0.74**	**-0.23**	**0.79**	-0.11	0.90	**0.48**	**1.62**	0.07	1.07	**0.13**	**1.14**	**0.36**	**1.44**	0.16	1.17
Club member	**-0.11**	**0.90**	0.04	1.05	**-0.22**	**0.80**	-0.03	0.97	-0.13	0.88	**0.13**	**1.14**	-0.19	0.83	**-0.25**	**0.78**	0.04	1.04
Dog owner	-0.08	0.93	**0.21**	**1.23**	-0.12	0.88	0.13	1.14	**0.36**	**1.43**	**0.55**	**1.74**	-0.09	0.91	**-1.09**	**0.34**	0.24	1.27
Fulltime work	**0.31**	**1.37**	0.11	1.12	**0.16**	**1.17**	0.05	1.05	0.07	1.08	0.12	1.12	0.00	1.00	**0.19**	**1.21**	-0.06	0.95
Household																		
N HH members	0.01	1.01	0.04	1.04	**0.08**	**1.08**	**0.17**	**1.19**	-0.05	0.95	**-0.10**	**0.91**	-0.03	0.97	0.00	1.00	**0.15**	**1.17**
High income	**-0.11**	**0.90**	**-0.20**	**0.82**	-0.12	0.89	0.02	1.02	**-0.15**	**0.86**	**-0.30**	**0.74**	-0.11	0.90	-0.05	0.95	**0.19**	**1.21**
Car usage																		
N vehicles	0.03	1.03	0.01	1.01	0.01	1.01	**-0.08**	**0.92**	0.01	1.01	**0.07**	**1.07**	**-0.03**	**0.97**	-0.06	0.94	0.00	1.00
Main car user	**0.17**	**1.18**	0.08	1.08	**0.28**	**1.32**	-0.16	0.85	0.25	1.28	0.13	1.14	0.21	1.24	-0.14	0.87	**-0.37**	**0.69**

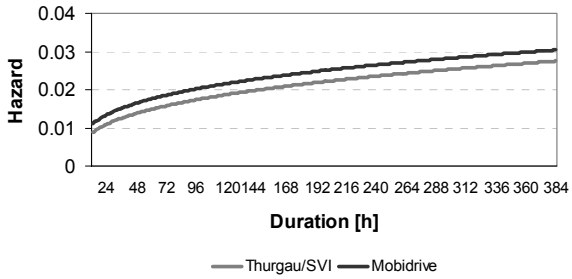
Area type																		
Frauenfeld	**-0.11**	**0.89**	0.12	1.13	0.03	1.03	**0.23**	**1.25**	0.00	1.00	-0.07	0.93	0.19	1.21	0.08	1.08	**0.15**	**1.16**
N	1525		561		1135		1035		609		857		319		781		1102	
Loglikelihood (0)	-1975		-704		-1518		-1446		-760		-1128		-458		-1094		-1524	
Loglikelihood (*β*)	-1882		-690		-1488		-1411		-738		-1086		-451		-893		-1439	
-2Chisquare	186		27		61		71		42		85		15		402		169	
Pseudo R^2	0.11		0.05		0.05		0.07		0.07		0.09		0.04		0.40		0.14	

Note: Dependent variable: Interval length in hours; RR: Risk ratio; **Bold**: Covariate significant at 0.05 level

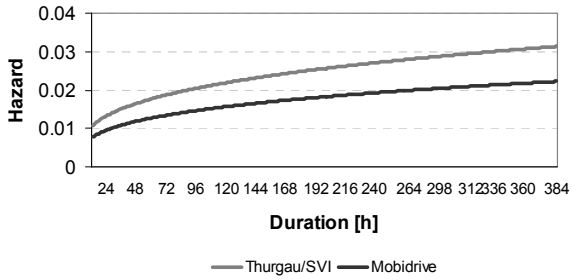
The Weibull distribution causes the above mentioned effects concerning the baseline hazard. For the exemplarily shown activities *daily shopping* and *active sports* (as well as for all other activity categories) it produces an increasing baseline hazard curve ($\gamma > 1$) which tends to be as good as constant soon after a few days (Figure 23). This should not be misinterpreted in the way that the nearly constant hazard indicates a regular demand over time with no significant rhythmic pattern. The rigid shape of the hazard is rather a result of the deterministic model structure which needs to be conceptually based by behavioural assumptions (as discussed above).

Figure 23 Exemplary baseline hazard rates by Weibull parametric duration model: Hazards at means of covariates

a) Daily shopping



b) Active sports



Note: intervals exceeding sixteen days are excluded)

Table 13 Summary of covariate effects fully parametric Weibull AFT model for Mobi*drive*

Activity type / Covariate	Daily shopping	Long-term shopping	Private business	Meet family / friends	Club meeting	Active sports	Excursion into Nature*	Stroll	Going out (bar, restaurant etc.)
Personal									
Male								-	
Age	-	-	+			-		+	+
Age^2	+	+				+			
Married				-				-	-
Parent	-		-		+	+		-	-
Club member			+			-		+	
Dog owner	-		+					-	
Fulltime working	+	+	+					+	
Household									
N household members			+		-	-	+	+	+
High income	-		-			+	+	-	
Car availability									
Number of vehicles		+				+			
Main car user				-	-	-		+	-
Type of area									
Karlsruhe						-		+	
$PseudoR^2$	0.06	0.04	0.05	0.06	0.09	0.16	0.29	0.41	0.09

+ increases interval length and decreases regularity
– decreases interval length and increases regularity

Note: Effects shown for all covariates statistically significant at the 0.05 significance level
* Model in total not statistically significant

Table 14 Summary of covariate effects fully parametric Weibull AFT model for Thurgau

Activity type / Covariate	Daily shopping	Long-term shopping	Private business	Meet family / friends	Club meeting	Active sports	Excursion into Nature	Stroll	Going out (bar, restaurant etc.)
Personal									
Male	+			+					-
Age	-			+	-				
Age^2	+			+	+				
Partner	+				-	+		-	-
Parent		-	-		+		+	+	
Club member	-		-			+		-	
Dog owner		+			+	+		-	
Fulltime working	+		+					+	
Household									
N household members			+	+		-			+
High income	-	-			-	-			+
Car availability									
Number of vehicles				-		+	-		
Main car user	+		+						-
Type of area									
Frauenfeld (town)	-			+					+
$PseudoR^2$	0.11	0.05	0.05	0.07	0.07	0.09	0.04	0.40	0.14

+ increases interval length and decreases regularity
– decreases interval length and increases regularity

Note: Effects shown for all covariates statistically significant at the 0.05 significance level

Han and Hausman results

The following tables present model estimation results using the statistical software package LIMDEP Version / NLOGIT 3.0 (Greene, 1998). While Table 15 (Mobi*drive*) and Table 16 (Thurgau) provide exemplary parameter estimates for the models "daily shopping" and

"stroll", Table 17 and Table 18 again give summaries of the direction of effects for all activity categories considered (the detailed model estimates for the other activity purposes may be found in the appendix A2).

The resulting effects of the covariates in the daily (grocery) shopping model for Thurgau are largely plausible and intuitive. The parameter estimates for the determinants sex, car availability, household size and fulltime-working are statistically significant and positive which means that daily shopping is done less or less frequent. The opposite is true for the covariates parent and high income. Together this makes clear that the group of male, highly mobile full-time workers shop significantly less regularity than for example mothers with a traditionally greater obligation for domestic work.

The "stroll" model shows exemplarily the effect of holding a dog as a strong fixed commitment with the covariate having a high statistical significance and a great coefficient. The pet forces the respondent by nature to go out for a walk with a high frequency and regularity. This underpins the necessity to include dominating pre-commitments of travellers in travel surveys to enable better explanations of routines and regularities. This was done in both, the Mobi*drive* and the Thurgau study.

Table 15 Exemplary ordered logit model results (Mobi*drive*)

Model	Daily shopping			Stroll		
Covariate	Coefficient	SE	P	Coefficient	SE	P
Personal						
Male	-0.02	0.08	0.83	-0.21	0.19	0.26
Age	0.00	0.01	0.92	**-0.05**	0.02	0.03
Age^2	0.00	0.00	0.81	0.00	0.00	0.17
Married	**-0.19**	0.09	0.03	-0.19	0.25	0.43
Parent	**-0.54**	0.09	0.00	**-1.10**	0.27	0.00
Club member	**0.19**	0.09	0.03	0.29	0.27	0.29
Dog owner	**-0.27**	0.10	0.01	**-2.25**	0.17	0.00
Fulltime working	**0.71**	0.09	0.00	**0.47**	0.21	0.03
Household						
N household members	**0.18**	0.04	0.00	0.10	0.09	0.27
High income	**-0.27**	0.09	0.00	**-1.16**	0.25	0.00
Car availability						
Number of vehicles	0.08	0.07	0.22	-0.03	0.19	0.87
Main car user	0.03	0.08	0.75	0.10	0.22	0.66
Type of area						
Karlsruhe	-0.02	0.07	0.78	**0.89**	0.20	0.00
Iterations completed		31			36	
N		3019			883	
Loglikelihood Constant		-5409			-1260	
Loglikelihood β		-5352			-1104	
-2Loglikelihood		115			310	
DF		12			12	
Prob. Chisquared		0.00			0.00	

Note: Dependent variable: Interval length in days; **Bold**: Covariate significant at 0.05 level

Table 16 Exemplary ordered logit model results (Thurgau/SVI)

Model	Daily shopping			Stroll		
Covariate	Coefficient	SE	P	Coefficient	SE	P
Personal						
Male	**0.43**	0.11	0.00	0.23	0.20	0.25
Age	-0.02	0.01	0.15	**0.74**	0.03	0.01
Age^2	0.00	0.00	0.25	**-0.94**	0.00	0.00
Partner	0.05	0.13	0.66	**-0.81**	0.26	0.00
Parent	**-0.80**	0.16	0.00	0.70	0.24	0.76
Club member	**-0-30**	0.10	0.00	**-0.44**	0.17	0.01
Dog owner	-0.01	0.14	0.92	**-2.46**	0.17	0.00
Fulltime working	**0.75**	0.12	0.00	0.13	0.20	0.52
Household						
N household members	**0.31**	0.06	0.00	**0.32**	0.08	0.00
High income	**-0.32**	0.11	0.00	-0.74	0.18	0.69
Car availability						
Number of vehicles	-0.01	0.04	0.88	-0.19	0.08	0.81
Main car user	**0.41**	0.16	0.01	-0.11	0.42	0.78
Type of area						
Frauenfeld (town)	-0.93	0.11	0.39	**0.42**	0.17	0.01
Iterations completed		31			36	
N		1526			781	
Loglikelihood Constant		-2987			-1261	
Loglikelihood β		-2937			-1119	
-2Loglikelihood		102			284	
DF		12			12	
Prob. Chisquared		0.00			0.00	

Note: Dependent variable: Interval length in days; **Bold**: Covariate significant at 0.05 level

Table 17 Overview of covariate effects of the Han and Hausman model (Mobi*drive*)

Activity type / Covariate	Daily shopping	Long-term shopping	Private business	Meet family / friends	Club meeting	Active sports	Excursion into Nature	Stroll	Going out (bar, restaurant etc.)
Personal									
Male					+		+		
Age							-	+	+
Age^2				+			+		-
Married	-								-
Parent	-	-	-	+	+			-	
Club member	+					-			
Dog owner	-		+					-	
Fulltime working	+	+			-		-	+	
Household									
N household members		+	+			+	+		+
High income	-		-			+	+	-	
Car availability									
Number of vehicles		+				+			
Main car user				-	-	-			-
Type of area									
Karlsruhe								+	
McFadden's Rho[21]	0.01	0.00	0.01	0.02	0.02	0.03	0.08	0.12	0.02

+ increases interval length and decreases regularity
– decreases interval length and increases regularity

Note: Effects shown for all covariates statistically significant at the 0.05 significance level

[21] The McFadden's is used to evaluate model fit. The value is a transformation of the likelihood ratio statistic intended to mimic R^2 values in logistic regression. Rho-squared values normally are lower than R^2 values (see e.g. Hensher and Johnson, 1981).

Table 18 Overview of covariate effects of the Han and Hausman model (Thurgau)

Activity type / Covariate	Daily shopping	Long-term shopping	Private business	Meet family / friends	Club meeting*	Active sports	Excursion into Nature	Stroll	Going out (bar, restaurant etc.)
Personal									
Male	+								-
Age		+						+	
Age^2								-	
Partner		-			-	+	-	-	
Parent	-	-				-			
Club member	-		-		-	+		-	
Dog owner					+	+		-	+
Fulltime working	+								
Household									
N household members	+	+		+	+			+	+
High income	-		-						+
Car availability									
Number of vehicles				-					
Main car user	+		+	-					-
Type of area									
Frauenfeld (town)				+				+	+
McFadden's Rho	0.02	0.01	0.01	0.02	0.01	0.02	0.02	0.11	0.03

+ increases interval length and decreases regularity
– decreases interval length and increases regularity)

Note: Effects shown for all covariates statistically significant at the 0.05 significance level
* Model in total not statistically significant

The overall picture of the covariate effects is not uniform. This is true for both, a comparison between the effects by the different model approaches and the comparison between the effects for the different survey data. The particular characteristics of the activity types lead to great

differences in the activity demand structure. In addition, it's likely that the chosen covariates only cover part of all possible determinants for the temporal structures of demand.

Nevertheless, general trends are the following:

- fulltime workers and persons with car availability show a less regular and less frequent pattern of activity demand for the shopping (both surveys) and private business activities (Thurgau),
- a converse trend for daily shopping is visible for respondents of high income households (both surveys/modelling approaches)
- intervals between some leisure activities are longer for members of larger households
- as could have been expected, parents (with children in household) need to go shopping on a (more) regular basis
- dog ownership significantly increases the frequency and regularity of strolls
- the city / survey area dummy has only few significant effects: for Mobi*drive* the Karlsruhe sample tends to be less engaged in the stroll activity; for Thurgau, the Frauenfeld respondents have a less frequent rhythm for going out (bar, restaurant etc.)

Summarising the results, these issues need to be stressed:

- The activities may be categorised into groups of daily respectively two-day rhythms and those with no fixed temporal structures of activity demand (this was shown in studies with a stronger focus on a classification of demand structures, too: Bhat, Srinivasan and Axhausen, 2003; Bhat, Frusti, Zhao, Schönfelder and Axhausen, 2004))
- The socio-economic impact on the temporal characteristics is visible but it does not seem to be a domination determinant within the activity demand structure.
- The activity demand structure is heterogeneous, i.e. there is no entirely clear picture for the chosen covariate effects. The results however indicate that factors which are generally strong for the explanation of travel demand (occupation status and car availability) play an important role for the prediction of the periodicity, too.

From a methodological point of view, the following can be noted: Allowing for the differences between the Weibull fully-parametric and the Han and Hausman model, the estimates are often similar to the results generated by the semi-parametric approach. The models are almost entirely significant but have only little explanatory power given the selected covariates (PseudoR^2/McFadden's Rho). This in fact raises the question of the strength of the random

variation effect in the regularity of the demand structure (see discussion at the end of the thesis).

*A comparison of the results with earlier analyses of inter-activity duration behaviour (using the Mobi*drive *data)*

As mentioned above the Mobi*drive* data was analysed in terms of regularity, rhythms and their determinants in parallel work using similar econometric techniques. Whereas Fraschini and Axhausen (2001) used Time Series Analysis to investigate the periodicity within the data, three studies applied advanced hazard models (Bhat, Sivakumar and Axhausen, 2003; Bhat, Frusti, Zhao, Schönfelder and Axhausen, 2004; Bhat, Srinivasan and Axhausen, 2005). The two latter ones yielded results which are well comparable with those found in this thesis. Furthermore, given the different techniques and depth of the investigations, the results correspond in many respects:

- The inter-activity duration for maintenance (grocery) shopping underlies a strong temporal regularity which is a similar finding to those of this study. The increase-in-demand concept proposed here could be widely confirmed. The time dependence for this particular activity type is interpreted as a depletion of inventory effect for food (Bhat, Srinivasan and Axhausen, 2005).
- Intershopping duration behaviour may be categorised into “regular shopping” and “random shopping” with an average spell between maintenance shopping activities of 3.6 and 1.8 days (Bhat, Frusti, Zhao, Schönfelder and Axhausen, 2004). An equivalent differentiation was not made in this thesis but could have been easily applied. Men, singles and members of households with high car-availability belong to the group of routine shoppers which show a low hazard for intershopping duration which was also found here.
- Other covariate effects had a stronger significance in the earlier intershopping duration studies than in this thesis. This is especially true for the covariates age, high income and accommodation type (i.e. living in a single house) (which was not considered as a covariate in this thesis), which all showed a negative impact on the hazard or – in other words – which lead to a less regular grocery shopping behaviour.
- For the other activities analysed, no clear time-dependence could be identified – which is in line with the results of this thesis –, however a weekly rhytmic pattern is prominent.
- Covariate effects are often similar between the studies. Fulltime workers show a generally lower frequency for household-related activities such as grocery long-term shopping. Members of family households were equally found to participate more in grocery shopping activities than in recreational ones which was parallely explained with their obsvious family and children obligations and committments.

– A point which was not considered in this thesis but which received strong attentention in the others is the issue of unobserved hetereogeneity. It could be shown that unobserved individual attributes contribute considerably to the differences in the inter-activity duration behaviour – however, to a different extent for the single activity types. The inclusion of unobserved heterogeneity effects is a modelling concern which becomes more and more important nowadays as preferences within groups of travellers tend to differ stronger than in the past (see also discussion in the concluding chapters).

7 The analysis of destination choice structures by the enumeration and listing of locations

The analysis of the rhythmic structures of activity demand is now complemented by the investigation of the temporal structures of destination choice and revealed activity spaces. The analysis will be based on two approaches: the *enumeration of trips and unique destinations* and a *continuous representation of space usage*. The latter approach is presented in Chapter 8. According to the structure of the preceding chapter, the approaches will be conceptually described at the beginning.

7.1 Enumeration of trips and destinations – an introduction

As a straightforward descriptive approach to reveal destination choice structures an enumeration exercise is introduced which will nicely show the ambiguity between stability and variety seeking in travel behaviour over time. The particular enumeration measures were developed in a series of papers by Schönfelder and Axhausen (2001; 2002; 2003a; b; 2004).

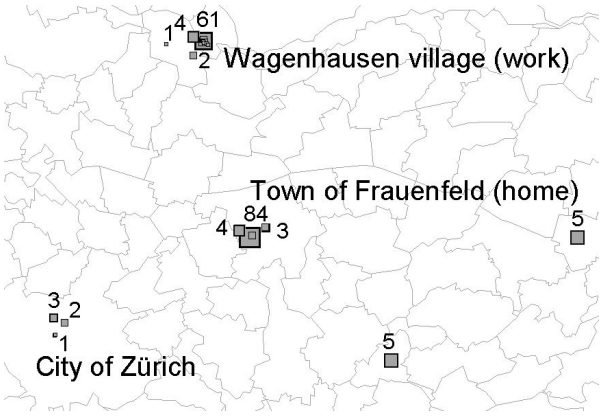
Figure 24 exemplarily shows how destination choice over prolonged periods might be represented. The combination of a unique geocode (coordinate) and purpose (if available) may be summarised either as a list offering the possibility to run a range of calculations, or as a map which represents a geographical visualisation of travel and activity space.

The listing of destinations – which has never been available in such detail before (an exception is Marble and Bowlby (1968) for retail travel) – allows to develop indicators which characterize temporal phenomena of destination choice. The variety of these indicators investigated in this work is summarised in Table 19. The indicators are described in more detail in the analysis section below.

Figure 24 Exemplary listing and graphical representation of destination choice over 6 weeks of reporting (Thurgau) – destinations by coordinate, purpose and frequency of visit

No.	x coordinate	y coordinate	Trip purpose	Frequency
1	708762	267791	10	**84**
2	705888	279774	5	**61**
3	717431	260326	8	**5**
4	728787	267812	8	**5**
5	705320	280030	8	**4**
6	708124	268234	8	**4**
7	696800	262922	8	**3**
8	705888	279774	3	**3**
9	709750	268430	8	**3**
10	697430	262617	8	**2**
11	705266	278898	3	**2**
12	705907	279831	5	**2**
13	705947	279672	8	**2**
14	708860	267906	6	**2**
15	709652	268433	6	**2**
16	676450	283500	8	**1**
17	696540	244786	8	**1**
18	696819	261863	3	**1**
19	696865	261899	8	**1**
20	703632	279585	8	**1**
21	705737	279582	8	**1**
22	705888	279774	8	**1**
23	705947	279672	3	**1**
24	706099	279624	8	**1**
25	706177	279561	3	**1**

cont.



* Female, 58, working fulltime

Table 19 Enumeration exercise: Indicators of destination choice over time

Phenomenon	Brief description of indicator
Volumes	Number of trips and unique locations visited
Stability/variability	Basic descriptives: Stability of departure time and mode choice
	Ratio between trips and unique locations
	Concentration of trips in a number of unique locations
Innovation rate and variety seeking	Number and share of locations previously not observed / actually visited
	Innovation rate: Share of unique places of the cumulative number of places visited
Dispersion and development of activity space size	Mean distance of observed locations from home
Clustering	Clustering of activities in nearby locations
Effects of pricing (Excursus based on Copenhagen data)	Combination of indicators

7.2 Analyses

This section will provide a selection of results based on the concepts shown above. As the number of proposed indicators and measurement approaches is large a concentration on the most interesting results was required.

7.2.1 Enumeration analysis

The enumeration exercise will start with the indicators described in Table 19 before turning to the application of this analysis approach to the Copenhagen road pricing experiment.

Trip rates

The number of trips and locations (*travel volumes*) is not an indicator of regularity per se, however, as travel volumes differ substantially between individuals and data sets, the amount of travel is believed to have direct impact on most of the following indicators. In addition, it may be assumed that the number of trips over a given time period will also affect the number of unique locations and their spatial distribution. Finally, the number of trips which can be expected over a period of several weeks has previously not been known and is an interesting quantity in its own right.

The trip rates across all modes mainly follow a Gamma distribution with zero as the lower limit of the underlying random variable (non-negative trip rates possible only)[22]. The median over all data set is about 23 trips per week which corresponds to cross-sectional results of 3 to 4 trips per day per traveller.

However, the distribution of numbers also shows the difference in trip rates between the data sources. The Thurgau travel diary data - based on a mainly rural but economically active survey area - shows by far the highest trip rates for all modes. The Uppsala and Mobi*drive* data differ only slightly for both mode categories which is interesting given the time gap of about thirty years between these surveys. The weekly as well as daily trip rate for the vehicles in Atlanta and Copenhagen is about 15%-30% higher in the (socio-economically unweighted) GPS

[22] Gamma distribution obtains highest score in probability distribution fitting using XPERTFIT (Law and Kelton, 1999).

data than those of regular car drivers[23] in the travel diary data. The difference in numbers is caused by the exact capturing of short car trips. In Borlänge for example, the average distance travelled per trip is only 3.8 km with average trip duration of about 6 minutes. In Mobi*drive* – with an admittedly larger local survey area – the corresponding figures are 21 minutes and 13 km. For Copenhagen the average trip duration is under 15 minutes which is small considering the size of the Greater Copenhagen agglomeration. In principle, the trip rates in the GPS observations need to be thought even higher than shown since the ad-hoc cleaning procedure erases (probably too) many of potentially correct short duration trips (see above). The relatively low Borlänge GPS trip rates are by some means an exception as not only the cleaning approach biases the number of trips (downwards) but also the systematic underreporting of out-of-area trips.

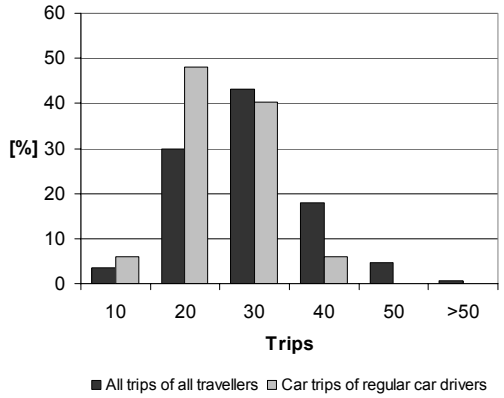
Table 20 Trips per week (details for Figure 25)

Study	Mean	Std.
All trips		
Uppsala	24.2	11.3
Mobi*drive*	24.4	8.8
Thurgau	28.2	9.2
Car trips of regular car drivers		
Uppsala	19.2	9.8
Mobidrive	19.9	6.8
Thurgau	22.3	8.4
GPS car trips		
Borlänge	19.2	8.9
Copenhagen	25.9	11.0
Atlanta	22.5	9.9

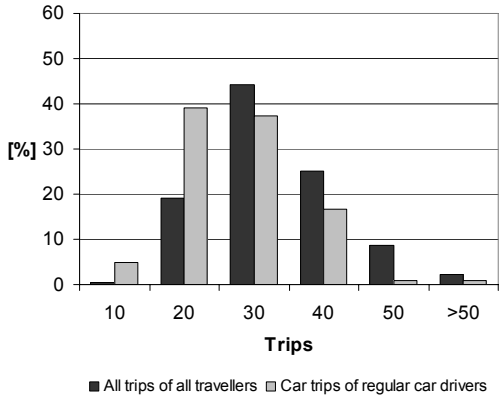
[23] For the travel diary survey data, respondents who made more than 50% of their trips by car are considered as "regular car drivers". This sub-sample acts as a comparison group for the GPS observations.

Figure 25 Mean number of trips per week (based on unweighted samples): distributions by mode

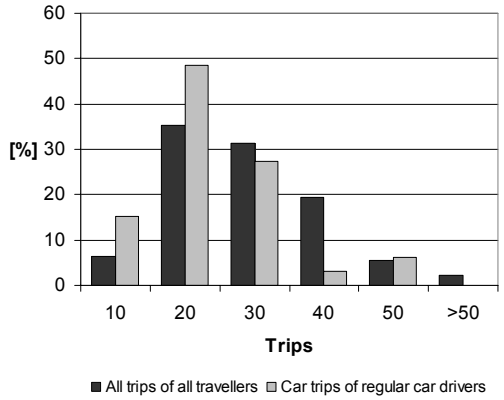
Mobi*drive* 6 weeks (n=317, 102 regular car drivers)



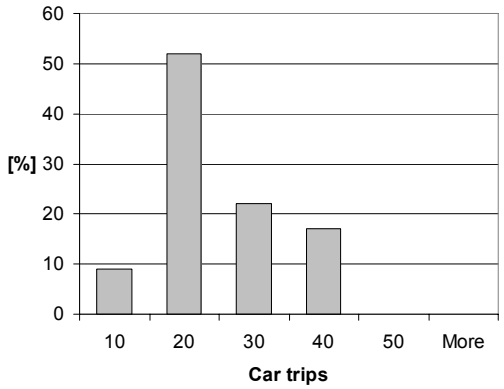
Thurgau 6 weeks (n=230, 102 regular car drivers)



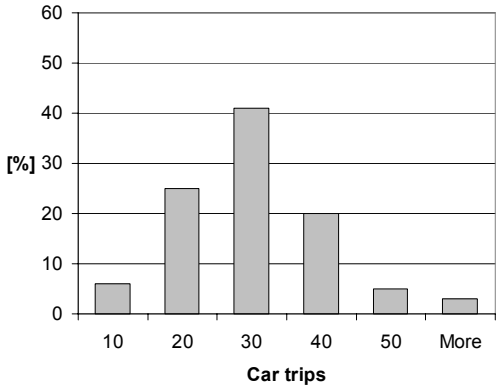
Uppsala 5 weeks (n=144, 33 regular car drivers)



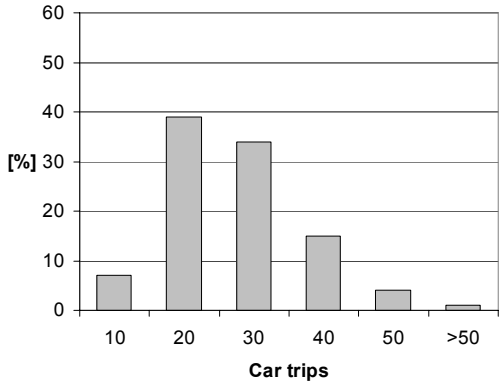
Borlänge (n=66 car drivers)



Copenhagen (n=200 car drivers; control period only)



Atlanta (n = 418 drivers)



Ratio of trips and unique locations

Stability and its counterpart *variability* in destination choice may be expressed by several interrelating indicators. The *ratio of trips to unique locations* is a good explanation of these phenomena as it shows the individual aspiration or requirement to vary locational choice given a certain number of trips.

The relationship of trips to unique locations was previously unknowable, as cross-sectional surveys cannot provide a credible estimate of this parameter. The available long-term travel data now permit an insight into this aspect of spatial choice behaviour. If the number of unique locations grows consistently with the number of trips, then variety seeking, for its own sake, becomes a credible explanation of these choices.

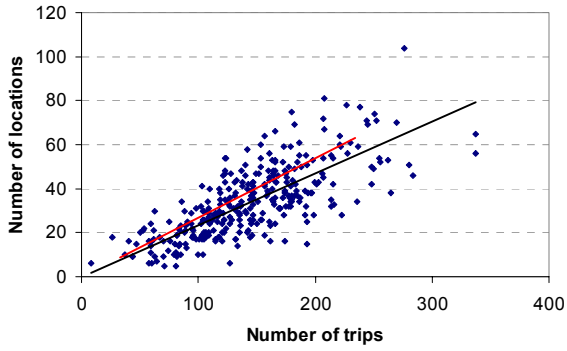
Figure 26 and Table 21 represent the ratios for the data sets analysed. It is interesting that the means are similar in spite of the differences of the survey techniques and backgrounds. The average ratio for the travel diary data varies in a narrow band, approaching about three to four trips to one unique location over time[24]. Travellers with regular or even permanent access and usage of cars show a more variable location choice behaviour which represents their greater opportunities in time and space.

The GPS observations deviate slightly from that figure indicating that the parameters of the cleaning and clustering processes used to identify unique locations need to be reconsidered for the observed trip ends. In all three cases, the parameter for the clustering (i.e. radius=200m) seem to be chosen too large as too few unique locations could be identified. Besides, the chosen cleaning thresholds obviously contributed to a misrepresentation of unique locations.

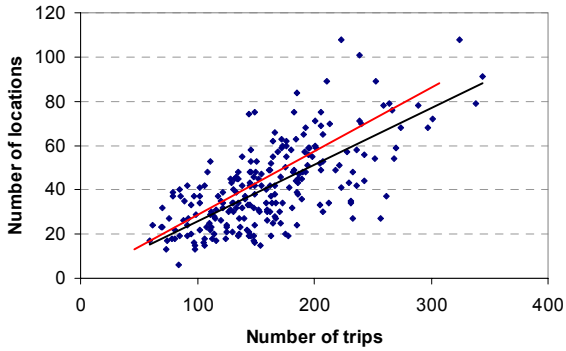
[24] This figure turns out to be the same for the travel diary data if the trips are stratified by mode of transport.

Figure 26 Relationship of number of trips and number of unique locations

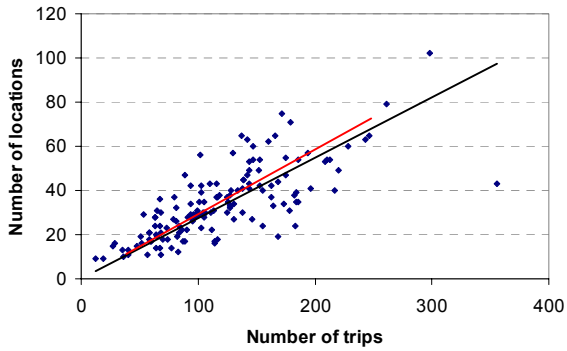
Mobi*drive*



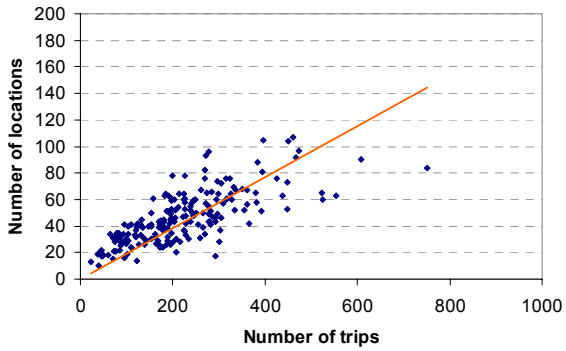
Thurgau



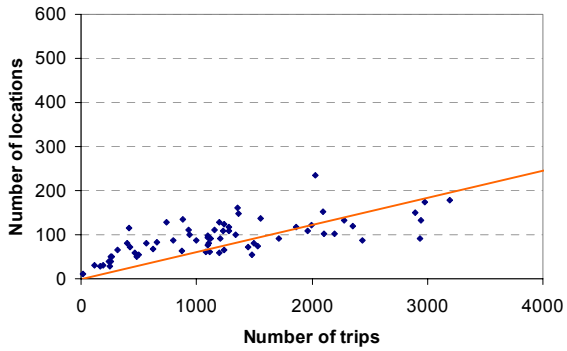
Uppsala



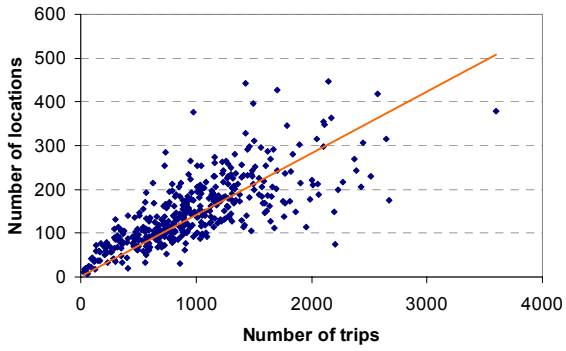
Copenhagen (n=200 car drivers; control period only)



Borlänge



Atlanta



Note: Dark line: Trend line all trips/locations, for comparison red/grey line: Trend line for car trips/locations of regular car drivers only

Table 21 Relationship of number of trips and number of unique locations (details for Figure 26)

		Scatter trendline (incept set to 0)		Unique locations – distributions			
		Slope	R^2	Mean	Std.	Skew-ness	Mean ratio locations to trips
Mobi*drive*	All	0.23	0.55	34	16	0.70	0.24
	Car trips of regular car drivers	0.27	0.63	31	15	0.78	0.27
Thurgau	All	0.26	0.46	41	19	0.88	0.26
	Car trips of regular car drivers	0.29	0.56	37	17	0.84	0.29
Uppsala	All	0.27	0.51	34	16	0.96	0.30
	Car trips of regular car drivers	0.29	0.62	29	15	1.93	0.32
Copenhagen	Car	0.19	0.34	46	20	0.76	0.24
Borlänge	Car	0.07	0.00	69	31	0.69	0.13
Atlanta	Car	0.14	0.47	148	77	0.95	0.17

An interesting question is if these ratios can be explained by survey background and/or socio-economic attributes of the travellers. Table 22 shows a stratification of the ratio for out-of-home travel[25] by survey and few selected socio-economic attributes. First of all, only few differences are visible for the overall averages between the Mobi*drive* and the Thurgau (0.40 unique locations per trip) which is in line with the above shown values. However, the socio-economic groups behave differently in the two surveys: Whereas in general there are much more homogenous ratios for the groups in Mobi*drive*, Thurgau shows much more distinct differences. In Mobi*drive*, the elderly and the self-employed have values above average which indicates a greater discretionary flexibility for the retired and an imposed flexibility for those who run their own business. Same results for the elderly respectively the retired can be found for the Thurgau data, too. Interestingly, for the younger respondents the data sets show great variations: Whereas in Mobi*drive* students are less spatially flexible than the average, in Thurgau it is the other way round. As most of the Thurgau based students are forced to travel long-distance to universities in Zurich, St. Gallen or even further, their activity spaces are obviously more disperse and variable than those of their counterparts from the big cities of Halle

[25] Note that by nature the ratios for out-of-home travel are substantially higher than those capturing all trips (including home directed).

and Karlsruhe (Mobi*drive*). German students often live close to their schools in student accommodations or shared flats. Thurgau pupils on the contrary are less flexible which mirrors the concentration of their travel between home and school. Finally, housemakers in Thurgau tend to behave spatially more flexible than the average. This mainly indicates that their travel behaviour is less tied to one main activity purpose (such as work or school) which usually attracts many trips to only one or few unique locations.

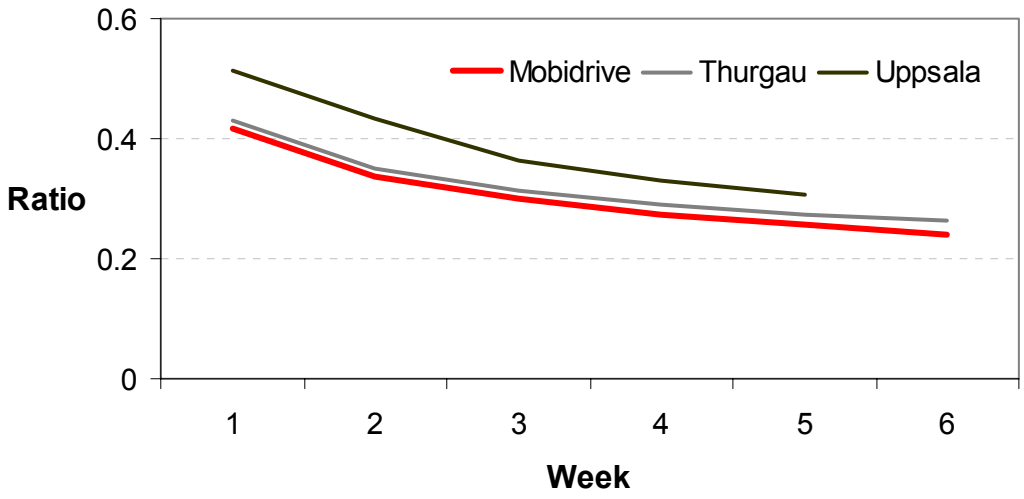
Table 22 Ratio between the number of unique places reported and the number of trips made over the six weeks of reporting: Non-home travel only (Mobi*drive*/Thurgau)

Attribute (N MD/TH)	Minimum		Maximum		Mean (Std.)		Median	
Survey	MD	TH	MD	TH	MD	TH	MD	TH
All	0.12	0.12	1.00	0.78	0.41 (0.13)	0.41 (0.13)	0.40	0.40
Sex								
Male (158/117)	0.13	0.13	0.68	0.12	0.41 (0.13)	0.41 (0.13)	0.39	0.39
Female (159/113)	0.10	0.13	1.00	0.18	0.41 (0.14)	0.42 (0.13)	0.40	0.40
Age group								
<18 (60)	0.11	0.12	0.68	0.52	0.40 (0.12)	0.32 (0.09)	0.41	0.32
18-35 (61)	0.21	0.20	1.00	0.63	0.39 (0.12)	0.40 (0.09)	0.38	0.39
36-65 (171)	0.10	0.18	0.68	0.76	0.41 (0.14)	0.44 (0.13)	0.40	0.44
>65 (25)	0.17	0.34	1.00	0.78	0.46 (0.15)	0.54 (0.13)	0.45	0.52
Occupation status								
Pupil (55/49)	0.13	0.12	0.74	0.52	0.41 (0.12)	0.32 (0.09)	0.41	0.33
Student (12/9)	0.16	0.36	0.54	0.63	0.34 (0.13)	0.45 (0.08)	0.33	0.45
Apprentice (11/11)	0.24	0.22	0.67	0.42	0.42 (0.13)	0.30 (0.07)	0.42	0.31
Housemaker (12/25)	0.20	0.20	0.55	0.69	0.39 (0.12)	0.47 (0.13)	0.40	0.49
Retired (53/20)	0.22	0.35	1.00	0.78	0.44 (0.14)	0.56 (0.12)	0.42	0.53
Unemployed (21/1)	0.20	0.36	0.63	0.36	0.41 (0.12)	0.36 (-)	0.42	0.35
Part-time working (29/-)	0.10		1.00		0.41 (0.16)		0.39	
Fulltime working* (111/115)	0.11	0.18	0.79	0.76	0.39 (0.13)	0.43 (0.12)	0.39	0.42
Self-employed (13/-)	0.29		0.72		0.46 (0.12)		0.43	

* Thurgau data does not allow to distinguish distinct working categories

Given the differences in the survey lengths, an exact comparison of these ratios among the surveys (as well as in principle for all other indicators shown in the following) is non-trivial. While it is straightforward to compare averages such as the mean daily trip rate or the mean daily distance by person, one needs to be careful with a direct comparison of the variability indicators in spatial choice if the length of the observation periods vary. In principle, stability might be less visible if a person is observed only few weeks (such as in Uppsala) than in long-duration surveys such as Atlanta with a monitoring period of one year or longer. Figure 27 represents the development of the ratio between unique locations and trips over time for the travel diary data sets. As one could expect, the ratio decreases with time as regular visits to places of daily life become more important with ongoing survey time. Hence, after only few weeks the ratio is dominated by frequently visited locations such as the work place rather than by "novel" places or better: places that had not yet been observed before (see discussion and analysis below). However, the analysis shows that after a sufficiently long period (about two to four weeks) of observation, the ratio approaches a fix value of about one location to four trips which seems to be a fundamental principle of daily travel.

Figure 27 Mean ratio of number of trips and number of unique locations by proceeding period



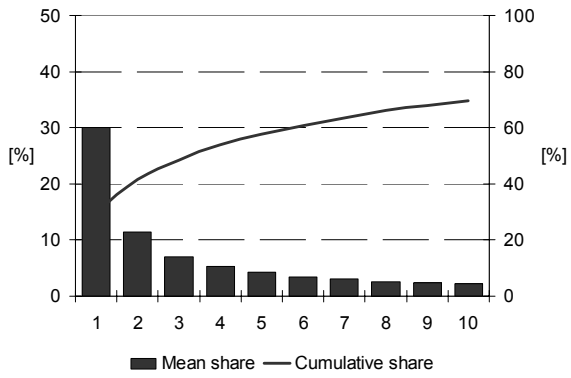
Concentration of trips in few locations

Although people seem to have many places they visit for different activities, this does not mean that each place is visited with the same frequency. People tend to *concentrate* their travel in a small number of locations which is predominant for particular activities within a given observation period. From a methodological but also from a planning point of view it seems interesting to know how many locations are necessary to know to describe a substantial part of a person's travel behaviour.

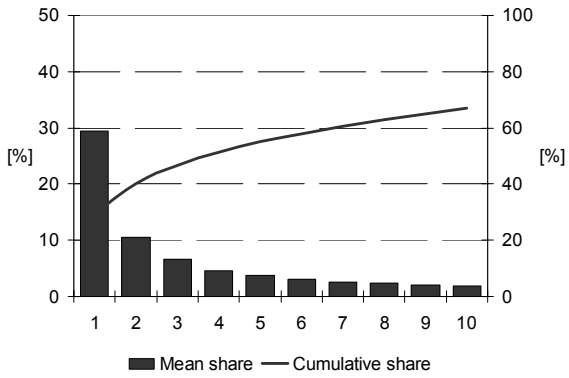
Figure 28 shows the average shares of non-home trips which are directed to the 10 most important unique locations identified. The cumulative share of for these first ten locations is about 80% of all trips in the travel diary surveys and between 40 to 60% in the GPS observations. Given the fact, that in total about 40% of all trips are home-directed (e.g. Mobi*drive*: 42%, Thurgau: 37% Copenhagen: 34%), this proves that over longer periods daily life is notably concentrated at few places only. This is relatively obvious considering that mainly work or education obligations still dominate daily activity and travel patterns for workers and students (Table 23).

Figure 28 Mean shares of trips to the ten most frequented locations (excluding home)

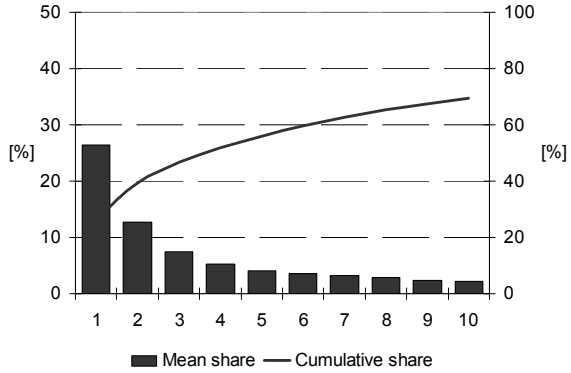
Mobi*drive* (all trips)



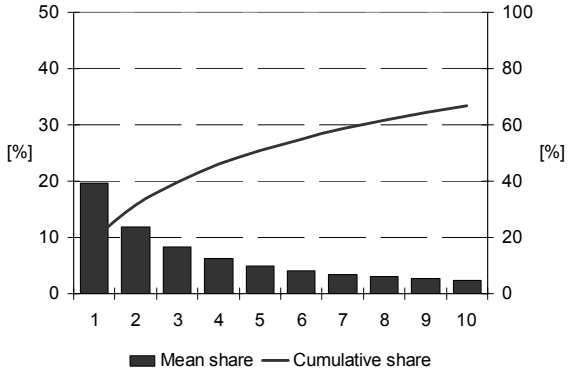
Thurgau (all trips)



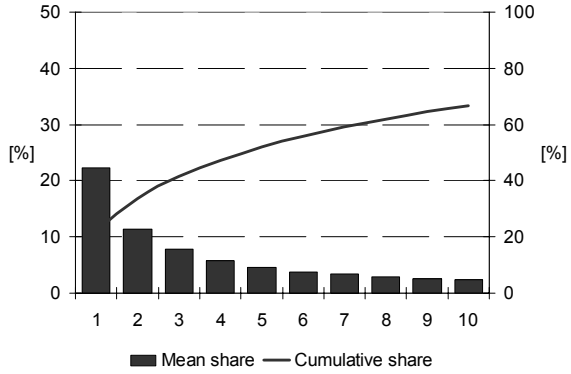
Uppsala (all trips)



Borlänge (car trips)



Copenhagen (car trips; control period)



Atlanta (car trips)

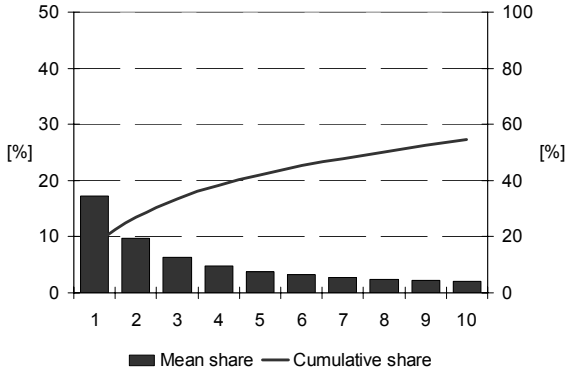


Table 23 Five most important trip purposes by occupation status and location (Thurgau)

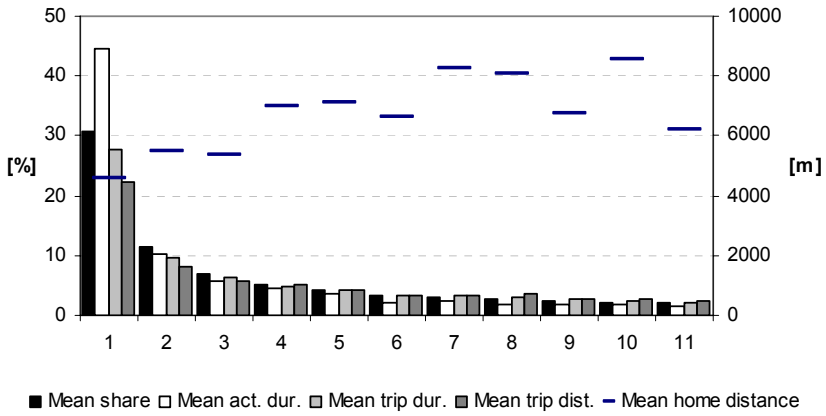
	Pupil		Student		Apprentice		Working		House-maker		Retiree		Unem-ployed	
	Purpose	Share	Purpose	Share	Purpose	Share	Purpose	Share	Purpose	Share	Purpose	Share	Purpose	Share
1	SE	98	SE	44	SE	45	WO	76	GR	44	LE	70	LE	100
2	LE	71	LE	44	SE	64	LE	48	LE	32	GR	45	LE	100
3	LE	96	LE	44	LE	55	LE	46	GR	40	GR	45	LE	100
4	LE	80	LE	56	LE	45	LE	35	LE	44	GR	40	GR	100
5	LE	80	LE	44	LE	55	LE	43	LE	40	LE	70	SP	100
N	49		9		11		115		25		20		1	

LE = Leisure, SE = School/education, WO = Work, GR = Grocery shopping, SP = Serve passenger

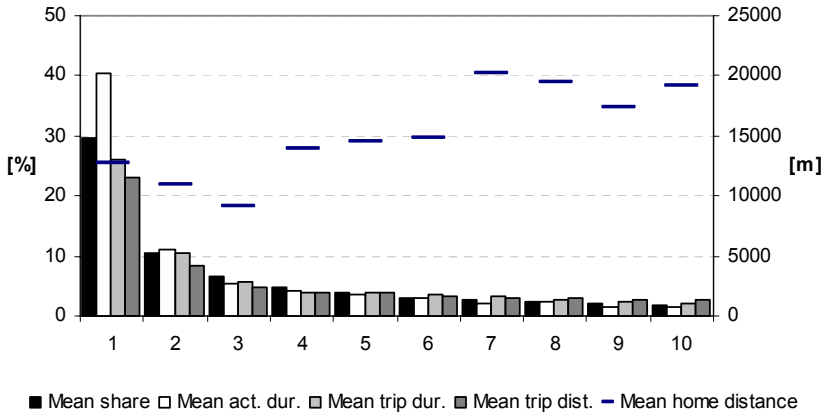
Another interesting question is how the most important places may be categorised in terms of durations and distances. Figure 29 indicates that the most important destination (apart from home) naturally absorbs by far the biggest share of activity duration whereas its share of trip distance and trip duration (of all trips made) is below its average of visiting frequency. The average share of trip distance however is mainly above average with decreasing importance of the destination. The same trend can be observed for the average distance from the travellers' home location which already provides an insight into the structure of activity spaces: Higher activity densities around the home location and lower densities at the edges of the activity space.

Figure 29 Mean shares of trips to the ten most frequented locations (excluding home), distances and durations

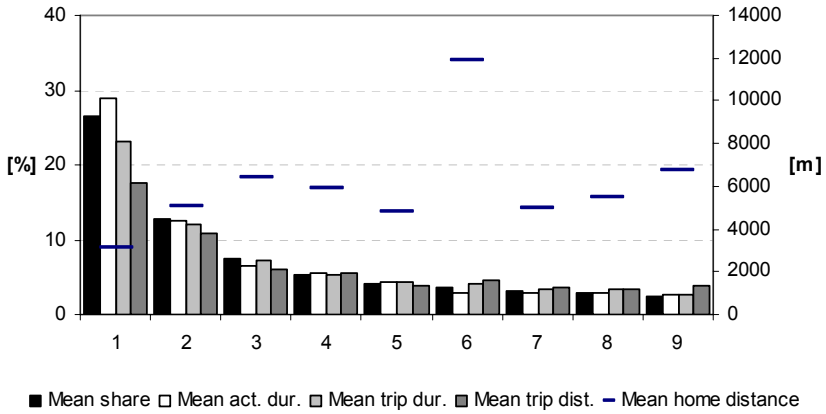
Mobi*drive* (all trips)



Thurgau (all trips)

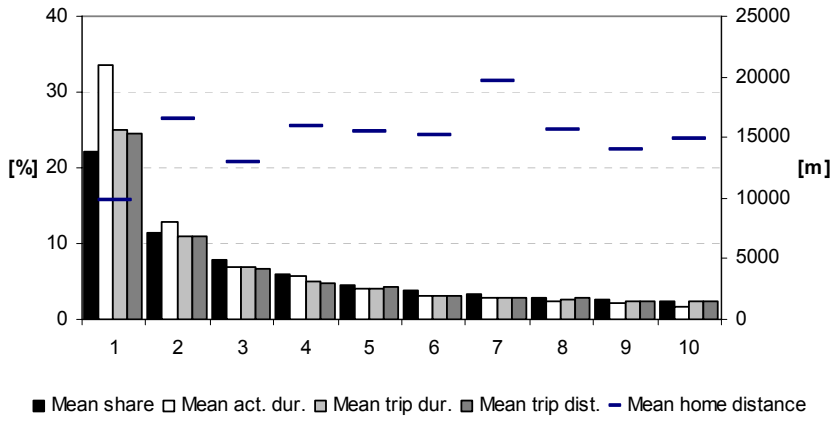


Uppsala (all trips)

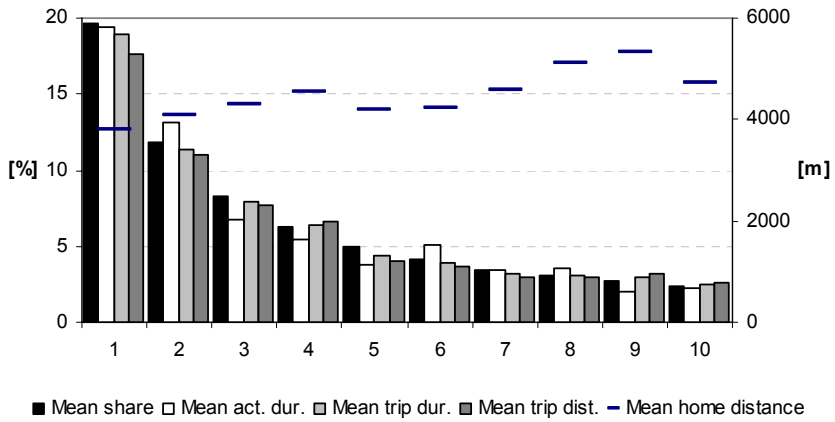


cont.

Copenhagen (control period; car trips)



Borlänge (car trips)



Note: Atlanta results not available

Mode choice for unique locations and departure time variability

Stability in mode choice for unique locations will first be represented by the Herfindahl index. The Herfindahl index or Herfindahl Hirschmann Index (HHI) is an often used measure of market concentration (see Herfindahl, 1950). The approach is also used in market research as an indicator for product loyalty of customers or groups of customers. Defining a travel decision such as mode choice as a market situation, the HHI may be used to characterize the stability in those individual choices, too. If we imagine a situation where a person repetitively travels to a certain place such as the work place over a prolonged period, then a high HHI

would indicate a "loyal" usage of a particular mode of transport to reach that particular unique location.

The HHI may be generally defined as the sum of squares of the market shares of each individual mode. As such it can range from 0 to 1 moving from equal distribution of all available modes to a domination of one travel mode for the combination of location and purpose. The HHI is given by

$$H = \sum_{i=1}^{n} (s_i^2) \tag{31}$$

where s_i is the modal share of mode i in the modal split and n is the number of travel modes considered

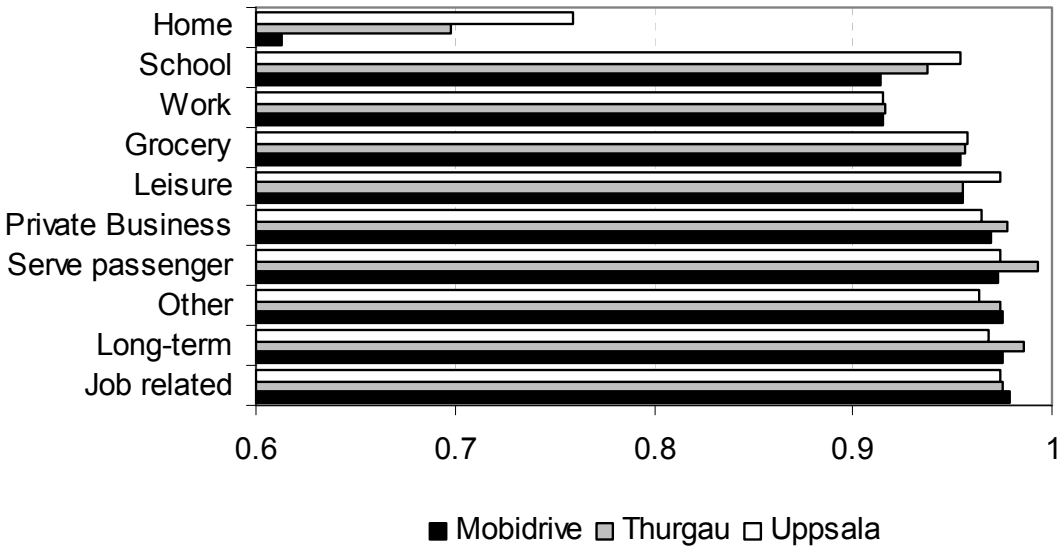
For this analysis, the single travel modes are aggregated into the categories “car” (car driver and passenger), “public transport” (train, tram, bus and other modes) and “slow modes” (walking and cycling).

Figure 30 shows the mean HHI by data set and purpose. It becomes clear that the stability of the combination unique location and travel mode chosen for all non-home purposes is large and approaches a HHI of 1 for most of the activity categories. Leisure and daily grocery shopping but in particular school and work show a slightly more flexible mode choice behaviour. This is an interesting result as these two compulsory purposes usually underlie more restrictions of choice. However, the stability of mode choice remains large and indicates first, the commitment and/or limitation of travellers to a single mode and second, a widely predetermined quality of modal accessibility of places. The comparatively low values for home represent the greater diversity of reaching one’s focus of daily (with almost half of all trips going there) and over and above the opposite side of the aggregate outcome for all the other activity categories.

The following results suggest a larger variability for the departure time choice for unique locations – however a direct comparison with the preceding findings on mode choice is difficult. Figure 31 gives the mean standard deviation of departure times for places with a unique combination of coordinate and purpose. As expected, less variability could be found for the compulsory activities work and school compared to the typically more flexible and occasional activities such as serving passengers or leisure (the Uppsala results deviate slightly as they do not show the distinct differences for the out-of-home activity categories.). The average standard deviation for school remains under an hour which nicely shows the fixed and coordinated structure of the education system.

In earlier analyses of the Mobi*drive* data, impressing representations of departure time stability were generated. Figure 32 shows the frequencies of respondents‘ first trip in the same interval within one working week (Monday to Friday)’ The base are all first trips of the day. The interval range is one hour whereas the intervals overlap by 45 minutes[26]. It can be shown that (by applying this *reduction* of the data) the stability of departure time choice gets obvious for the morning peak and in particular for socio-economic groups with activity programmes tied to strictly scheduled activities (here: school/pupils). The opposite is true for groups which are less focused on obligatory or scheduled activity types (retirees).

Figure 30 Mode choice stability by purpose represented by HHI: Mean values by purpose (sorted by Mobi*drive* values)



[26] Example: A person leaves home in one week three times at 7:50 and twice at 8:20. This week is counted in the intervals 7:00-8:00, 7:15-8:15, 7:30-8:30 and 7:45-8:45 in the category “3 frequencies“ and it is counted in the intervals 7:30-8:30, 7:45-8:45, 8:00-9:00 and 8:15-9:15 in the category “2 frequencies”.

Figure 31 Departure time variability: Median standard deviation of departure times (of most important unique location of each purpose) (sorted by Mobi*drive* values)

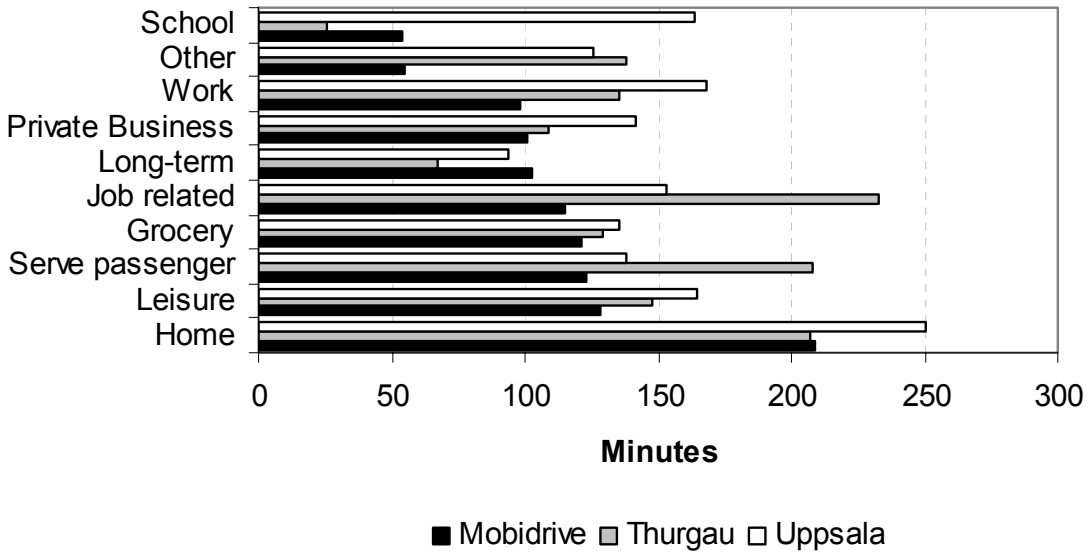
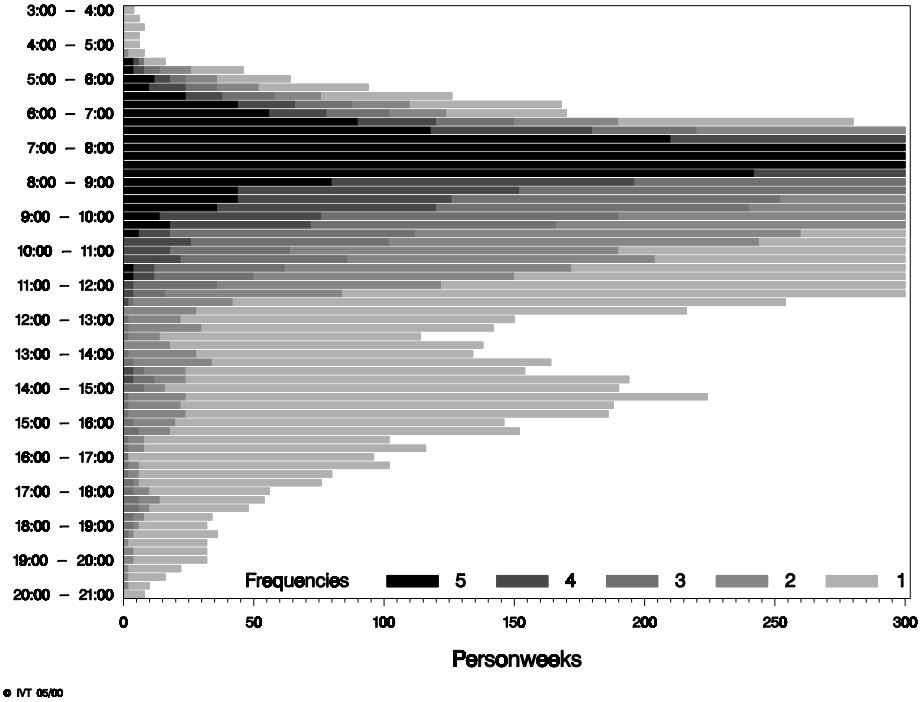
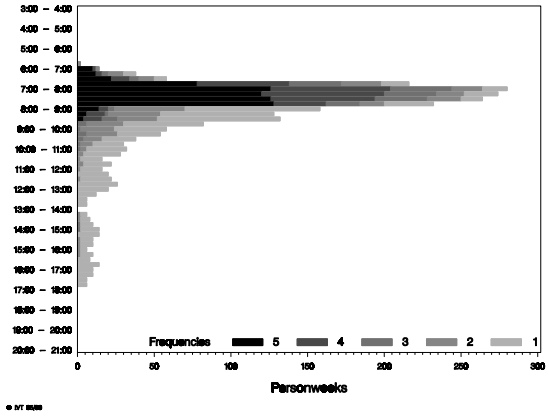


Figure 32 Frequencies of first trip in the same interval over the working day of one week – by selected occupations (one hour intervals starting every 15 minutes)

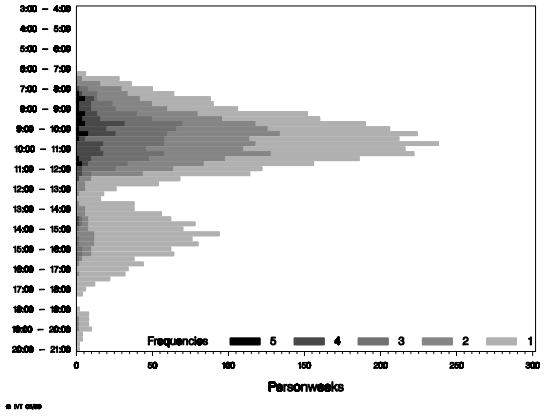
All respondents



Pupils



Retirees



Source: König (2000) 66ff.

Innovation aspects

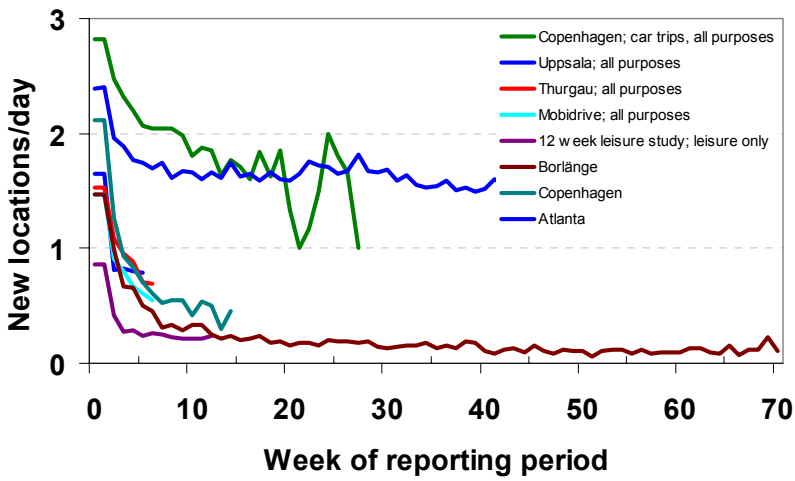
This (preceding) and other earlier analyses of the temporal aspects of travel have already shown that there is strong regularity in individual travel behaviour but against a background

of substantial variability (e.g. Schlich, 2004 and references there). The question arises therefore if this is also true for the locations visited. Or in other words, do people have a restricted number of places they know and visit? *Variety seeking* is a likely motive for travellers to "discover novel" or better previously not visited places over a time period. An initial approach to reveal this trend is to identify all those locations which were previously unobserved in the course of the observation period.

The following graph shows the average number of additional locations per day that had not yet been visited previously during the survey periods. It seems that there is an almost unlimited number of places people know or need to discover, because even after many weeks there are still places people travel to for the first time.

In the long run, the GPS observations show averages of about 0.2 (Borlänge) to 1.5 (Atlanta) previously not observed locations added per week. The real value is probably closer to the above range (one to 1.5 new locations per week) as the Borlänge results refer only to the rather limited observation area of the Borlänge study.

Figure 33 Comparison of studies: New locations/day (home excluded)



Of course, the term "new" or "novel" location is a misnomer, as people have some activity locations which they visit with very low frequency, such as for example the dentist. These loca-

tions are not genuinely new or previously unknown. In the two Swiss surveys (Thurgau and Leisure study), the respondents were asked to identify, if they had ever visited the place before, and if yes, how often. Compared to the detection of previously unobserved places, this information yields a more reliable indicator of innovation and variety seeking.

Combining this with the previous analysis, it becomes clear that most of the "added" locations shown in Figure 33 are not genuinely new. Still, there is steady number of actually never before visited, truly new locations. In the Thurgau data (Figure 34), the mean of the latter number is 0.30 locations/day (Std.: 0.1) for all days and purposes over the six-week reporting period. The Saturday even shows a higher mean with 0.42 novel places visited (Std.: 0.13) whereas the Sundays yield an average below all weekdays with 0.26 (Std.: 0.08).

Especially leisure travel contributes to the amount of new locations discovered over time. On average, 53% of all previously never or only seldom visited locations are leisure places (dotted line in Figure 34). Similar results could be found in the Leisure study (Figure 35). The mean for genuinely new locations (defined by post code and purpose) added per day and person over the twelve weeks of reporting was 0.37 (Std.: 0.18). From a more aggregate perspective (Figure 35, bottom), about 10% of all leisure places visited during the survey period were previously unknown to the respondents.

Figure 34 Thurgau: Mean number of previously not observed locations per day and mobile person and share of actual visiting frequency

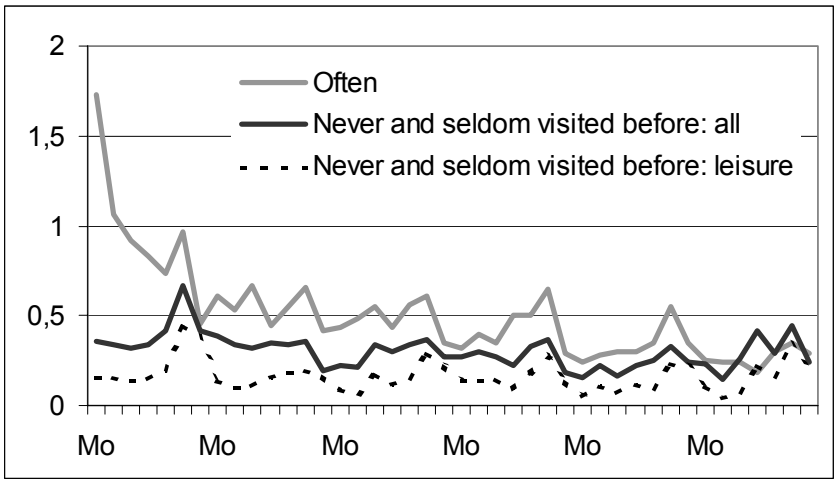
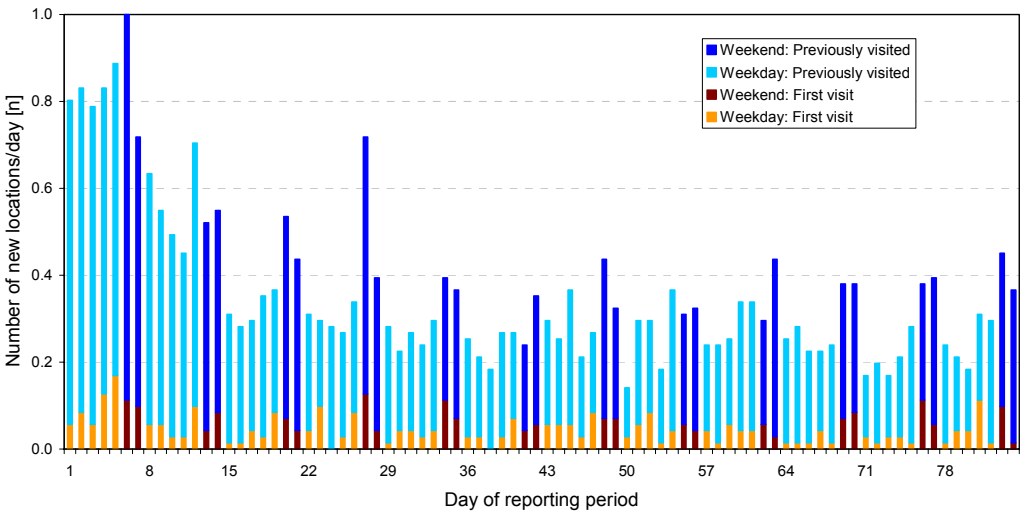


Figure 35 Leisure study: Innovation in locational choice

Mean number of previously not observed locations per day and mobile person



Frequency of previous visit of the location

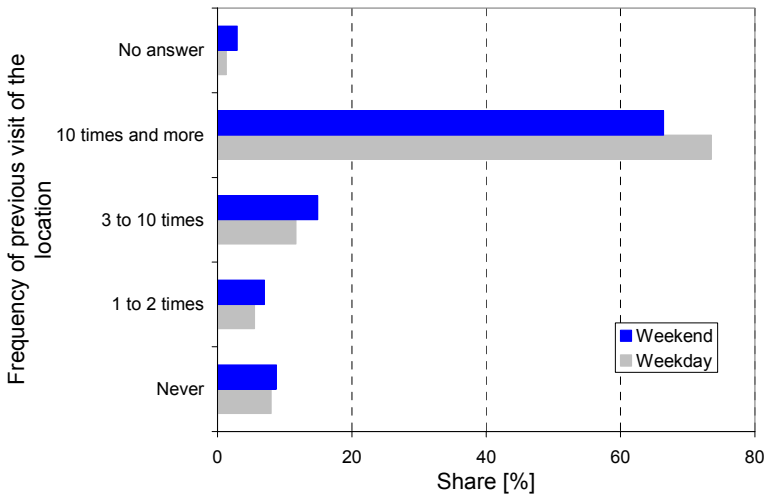


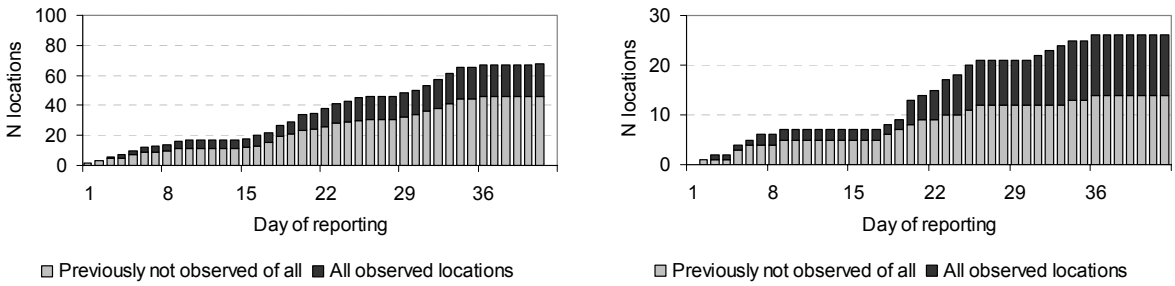
Figure 36 shows another interesting aspect innovation in destination choice for two exemplarily chosen Thurgau respondents. It represents the cumulative number of all locations visited over the period of reporting and the cumulative number of those which were previously not observed. It can now be assumed that the higher the share of the latter number, the greater the aspiration (or need) of the traveller to vary destination choice. Those two exemplary persons

show substantially different "innovative behaviour" with the male traveller having a much greater flexibility than the female example (bottom).

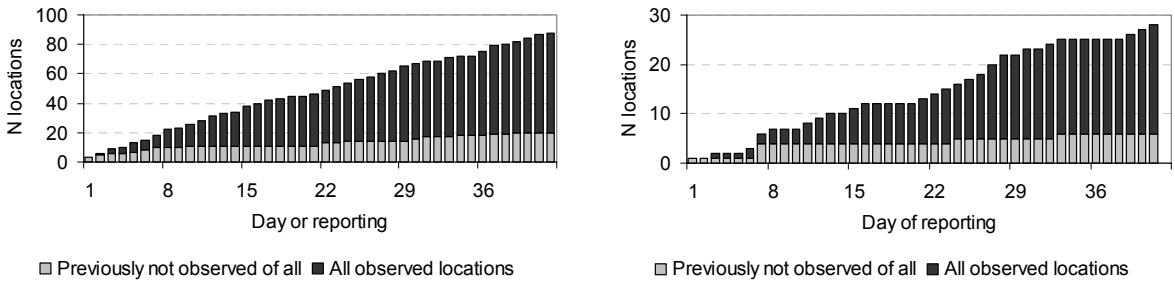
Figure 36 Individual characteristics of variety seeking in locational choice – two examples (Thurgau sample)

All activities	Leisure activities only

Person 1: Male, 53, fulltime working



Person 2: Female, 38, part-time working



The results on previously not observed or visited places provoke the question if these "new" or at least unobserved locations are added to the personal standard destination repertoire. The aspiration to search for new places does not necessarily mean that those places are built into the daily activity space. However, this issue can often not be addressed explicitly (as the respondents have not been asked to provide such information), but a simple listing of

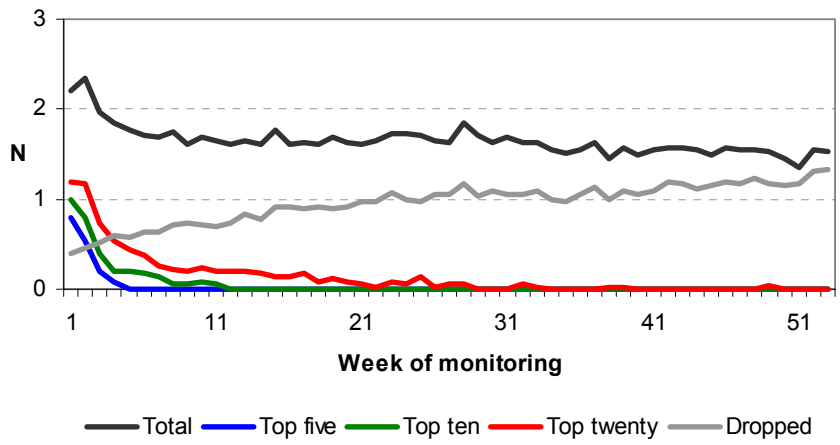
- the total number of locations not previously observed
- the number of locations which are added to a pre-defined standard locations repertoire, and
- those which are visited only once in the long run ("dropped places")

will provide evidence of the "*binding effects*" in destination choice.

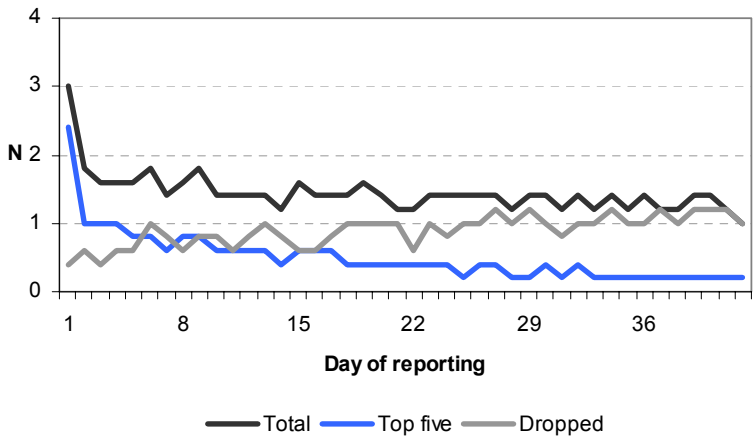
Figure 37 shows the total number of locations not previously observed, the locations which are added to a pre-defined standard locations repertoire, and those which are visited only once in the long run ("dropped places"). The standard sets represent the 5, 10 and 20 most visited places over the total survey period. Unsurprisingly, the average share of dropped places increases steadily with ongoing time. Clearly, less new places "get the chance" to become a regularly visited destination. However, the standard destination repertoire of a traveller becomes visible already after a few weeks (see long GPS observation), which is interesting in terms of future survey design procedures. In other words, it takes about five to ten weeks of monitoring (see also Mobi*drive* for comparison) to gain relative certainty about individual destination choice preferences. Given the complexity of daily life, this is a fairly small number (see also conclusions).

Figure 37 Number of "new", unobserved locations per monitoring day by week respectively by day of reporting (Mobi*drive*)

Atlanta



Mobi*drive*



Dispersion of the activity space

The spatial distribution of destinations will be the key matter of analysis in the continuous space representation section, however, the level of *dispersion* and – as a consequence – the *development of activity space sizes* over time can be also shown by the following enumeration exercises. As a straightforward indicator of dispersion, we choose the average (crow-line) distance of the locations from home. As already mentioned, home is by far the most important

centre of daily life and acts for most travellers as the hub for obligatory as well as discretionary travel (see e.g. Ellegård and Villhelmson, 2004). By calculating the individual mean distance of places from home, one gets an impression about the approximate extent of individual activity spaces.

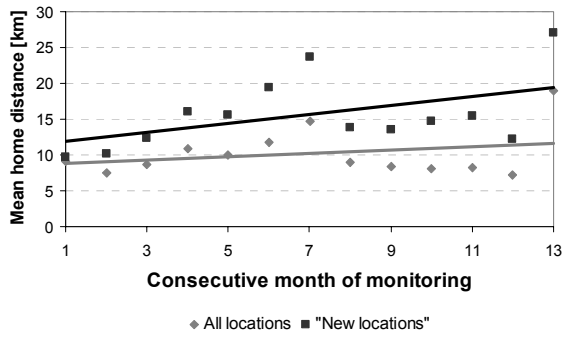
If turning to the *development of activity space sizes over the reporting period,* one may develop two hypotheses: First, "new" locations tend to be chosen further away from home as for example variety seeking aspirations in spatial choice values closer locations less than those further away from one's centre of life. This is especially true for leisure. Second, even though this trend might be observed, the temporal development of day-to-day activity space size is rather stable given the set of time, space, speed and social coordination restrictions one has to face (Hägerstrand).

The Atlanta data (Figure 38, left) shows that on the aggregate level these hypotheses can be confirmed. The home distance of "so far undiscovered" places is substantially higher than for all unique locations visited. The average home distance (whole sample) of new locations is even increasing over the monitoring period (see linear trend line with a slope of 0.61). However, the average home distance of all places remains more or less the same, with no visible increase in the spatial distribution of places.

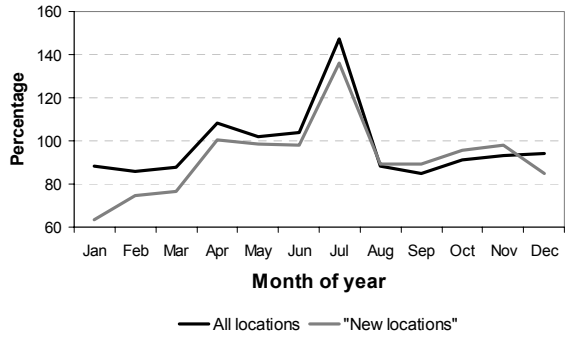
A side product of the analysis is an indication of how seasonality affects destination choice (Figure 38 (right)). If the monthly deviation of home distance from the yearly mean is calculated, we find that the spring and summer months yield a significantly more disperse choice of locations than the other months of the year – again an indication of variety seeking in spatial behaviour. This is true for the so far undiscovered as well as the total of places visited.

Figure 38 Development of activity space size: Average distances of locations from home

Mean distance from home by month of monitoring



Percentage of mean distance from home by month of year (sample average)



Clustering activities

One other interesting issue in locational choice is the question whether and how intense travellers *cluster* their activities at subcentres of their activity spaces. It is assumed that destination choice is determined by the needs, obligations and fixed commitments of the travellers and that activity demand is therefore satisfied at few focal points of daily life. In order to minimise travel times and distances, people tend to group their activities at few places of locational proximity and density which may be in the vicinity of home or other pegs of daily travel.

Table 24 shows that a large majority of the respondents of analysed surveys behave this way. Given a rather rough definition of a cluster, i.e. a common catchment radius of 1000m crow-fly distance, a minimum of 10% of all trips directed to the cluster and at least three unique locations associated with it, most of the travellers have at least one of such distinct centres of daily life[27]. The statistics provide some indication that the number of clusters is larger for respondents of smaller places (Borlänge, Uppsala) which represents the greater compactness and better accessibility of towns in contrast to bigger cities. Besides, the number obviously increases slightly with the length of the reporting period which might be biased though by the GPS data cleaning procedure which does not create the real number of unique locations.

However, the total number of clusters never exceeds five even after up to 50 weeks of monitoring or more such as in Borlänge and Atlanta.

Table 24 Share of respondents having spatial clusters [%]

Number of clusters	0	1	2	3	4	Median	Mean	Std.
Mobi*drive* all (317)	13	42	38	6	0	1	1.4	0.8
Car trips of regular car drivers (102)	29	44	22	4	1	1	1.0	0.9
Thurgau all (230)	9	45	36	10	0	1	1.5	0.8
Car trips of regular car drivers (102)	29	39	25	6	0	1	1.1	0.9
Uppsala all (144)	3	31	50	14	2	2	1.8	0.8
Car trips of regular car drivers (33)	6	33	21	36	3	2	2.0	1.0
Copenhagen (control period) (200)	12	36	33	18	2	2	1.6	1.0
Atlanta (418)	11	34	40	13	2	2	1.6	0.9
Borlänge (66)	2	23	39	30	6	2	2.2	0.9

Note: Clusters defined by: Catchment radius 1000m, minimum 10% of all trips in cluster, minimum three unique locations associated with cluster

Using the same definition, it becomes clear that activity clusters evolve to a large extent around the home location. This again underpins the importance of home for one's activity patterns. In the Mobi*drive* study, more than half of all cluster centres, i.e. the core defined by the most important location in terms of visiting frequency, are home whereas other activity purposes are only of little importance (Table 25). There seems no indication that for example the workplace and the surrounding area play a significant role for the efficient combination of work and the rest of the activity spectrum of activities in eventually distance minimising clusters.

[27] The clusters were generated using a nearest centroid sorting cluster method (Anderberg, 1973) which is implemented in the SAS software package.

Table 25 Internal structure of activity spaces: Activity cluster cores

Purpose	Mobi*drive* all	Mobi*drive* fulltime	Thurgau all	Thurgau fulltime	Uppsala all	Uppsala fulltime
Home	55	57	43	42	44	44
Leisure	12	11	14	10	12	12
Work	11	24	15	22	18	25
School	8	1	8	11	0	1
Daily shopping	6	4	9	5	19	12
Private business	5	0	3	1	2	1
Long-term shopping	1	1	0	1	1	0
Serve passenger	1	1	4	4	2	3
Work related	1	0	4	4	0	0
Other	0	1	0	0	2	2

* Note: Results only available for travel diary data as trip purposes have not yet been imputed for GPS observations

If home is such a central anchor of daily life, it seems interesting to explore which and how intense other activities are performed in a walking distance from that point. Table 26 shows for Mobi*drive*/Karlsruhe that within a radius of 1000m from home (crow fly distance) – 70% of all observed walking trips fall within this distance class – a big share of the inner-urban daily travel can be found. Even considering the great variability between the respondents (see large standard deviations) and the differences between the infrastructural qualities of their home vicinities, it can be stated that recreational as well as private business and shopping activities are tied to home. As shown earlier (Rindsfüser, Perian and Schönfelder, 2001, 98ff.), there are differences between the certain socio-economic groups for the level of close-to-home activity performance. Whereas putatively less mobile persons such as pupils and the unemployed make intensive use of the home's surrounding area for example for leisure activities, the highly mobile persons such as the self-employed and student tend to have a significantly more disperse activity location choice for leisure. Table 26 also shows that the vicinity of the workplace obviously absorbs only few daily trips which is especially true for leisure and daily shopping.

Table 26 Activity demand in the household location's neighbourhood, Mobi*drive*/Karlsruhe

	Maximum of distance from location: 1000m														
	Home							Workplace*							
	Respondents who reported the respective activity	Share (all activities of that type) [%]	Std.	Share duration [%]	Std.	Share expenditure [%]	Std.	Respondents who reported the respective activity	Share (all activities of that type) [%]	Std.	Share duration [%]	Std.	Share expenditure [%]	Std.
Private busin., admin.	60	**70**	43	67	46	16	37	24	**4**	20	4	20	0	0
Group/club meeting	89	**45**	46	44	46	31	45	32	**3**	18	3	18	3	18
Daily shopping	149	**47**	32	40	34	43	37	59	**13**	22	13	23	12	23
Other	39	**44**	47	42	47	5	22	13	**12**	31	13	32	15	38
School	53	**42**	48	42	48	14	35	10	**10**	32	10	32	0	0
Private business, other	156	**32**	29	29	32	26	38	60	**13**	23	11	22	13	29
Walk or stroll	107	**29**	41	27	42	3	17	40	**6**	19	3	14	5	23
Meeting friends	146	**26**	32	22	30	4	19	57	**3**	9	2	7	0	0
Active sports	93	**25**	35	25	36	13	32	31	**8**	25	8	25	0	0
Serve passenger	110	**24**	35	21	36	6	22	42	**11**	26	9	24	3	17
Going out at night	137	**18**	28	17	28	15	31	54	**13**	25	11	22	10	22
Excursion (culture)	68	**15**	34	14	34	8	27	30	**13**	32	13	31	12	32
Long-term shopping	150	**13**	22	9	19	9	21	58	**14**	26	12	25	14	29
Work related	68	**13**	30	13	31	4	16	36	**24**	36	21	37	12	32
Garden/cottage work	36	**12**	28	9	25	3	17	16		0	0	0	0	0
Meeting family	17	**12**	33	12	33	0	0	9	**11**	33	11	33	0	0
Window shopping	52	**12**	31	7	25	8	27	17	**18**	39	18	39	13	34
Work	82	**11**	30	11	30	4	20	61						
Further education	27	**8**	27	8	27	0	0	9	**7**	22	5	15	0	0
Excursion nature	68	**4**	21	4	21	0	0	25	**1**	7	0	0	0	0

* Only for the group of respondents of which the second most important location is the workplace

Whereas it is interesting to note that the travellers' homes still act as an important anchor point of daily life, it can be shown that there is significant variability between the Mobi*drive* respondents. One of the reasons for that is certainly the difference between the quality of supply of shopping and other opportunities around the particular home locations. Exact information about the supply of opportunities and the infrastructural quality of the travellers' home areas is still difficult to obtain in travel survey settings. Fortunately, for Mobi*drive* it was possible to obtain selected geocoded point-of-interest data for Karlsruhe using ordinary Yellow-page business addresses and a geocode engine for digitalisation. The data sets covers about 3000 leisure, shopping and administrative facilities in the Karlsruhe region. Using this data set and the general information about the home locations' population density as indicators for the level of supply, it could be found that there exists a significant relationship between supply and demand for daily shopping (Table 27). The number of shopping trips to the home area (within a radius of 1000m) as well as the shopping trips made by "slow modes" (walk and bicycle) increases with better shopping supply and higher density. Even considering the initial character of this analysis which should be deepened in more sophisticated destination choice models, the trend seems clear and confirms land-use policy's approach to strengthen residential areas as centres of daily activity demand.

Table 27 Pearson correlation coefficients between selected home based supply of shopping and shopping trip demand (Mobi*drive*/Karlsruhe)

	Number of shopping opportunities within radius of 1000m from home	Share of shopping trips performed within a radius of 1000m from home	Share of shopping trips performed within a radius of 1000m from home by slow modes
Population density of home location surroundings (building block level)	0.64	0.26	0.26
Number of shopping opportunities within radius of 1000m from home		0.26	0.27
Share of shopping trips performed within a radius of 1000m from home			0.83
N	149	149	149

All correlations shown are significant at the 0.05 level (2-tailed). Shopping opportunities involve bakeries, butchers, chemists, local grocery stores and supermarkets.

Copenhagen road pricing experiment – some results on changing travel behaviour due to pricing

Finally, some exemplary results on the changes in destination choice within the Copenhagen pricing experiment are provided. As an excursus to the actual enumeration exercise, this short section combines the analysis of activity spaces based on long-duration data sets with the analysis of the efficiency of transport policy measures.

One of the appealing features of the Copenhagen GPS data is the possibility to examine the differentiated pricing system applied against its impact on personal mobility. This short analysis goes into the question of how road pricing especially impacts destination choice. The panel structure with multiple observations for single cars/drivers allows to investigate the diversity of individual activity repertoires and related travel patterns in both, control and the pricing periods. A larger range of such analyses based on the Copenhagen data – which were

inspired by the investigation framework of this thesis – can be found in Schönfelder, Rich, Nielsen, Würtz and Axhausen (2005).

This investigation includes respondents who had (at least) a control and a pricing period. The main travel characteristics of the resulting data set are given in Table 28. They show that the virtual charging has a – partly statistically significant – impact on travel behaviour. The reduction in trip rates and daily travel distances are obvious for the high kilometrage scenario with a decrease of about 6 to 10 percent. For the two other pricing combinations the results are ambivalent. Similar results were found in earlier studies of AKTA using a different subset of the data base for analysis (Nielsen and Jovicic, 2003; Nielsen, 2004).

Table 28 Copenhagen GPS data: Travel volumes and distances by pricing period

Combination of pricing periods	Mean number of trips/day		Mean daily distance [km]	
	Control	Pricing	Control	Pricing
Control – High	4.3	**4.2**	32.1	**29.9**
Control – Low	4.4	4.4	38.4	39.3
Control – Cordon	4.1	4.2	31.0	29.8

Note: Means based on mobile days
In **bold**: Significant difference in means (T-Test); p = 0.05

For part of the further analysis the GPS data was grouped into regular and non-regular trips. To identify regular or routine trips, the data was clustered by departure time, day of week (Monday to Friday, Saturdays and Sundays) and stop duration using a suitable cluster methodology (SAS FASTCLUS; Anderberg, 1973). A trip was defined as regular when it belongs to a cluster with at least ten or 3% of all non-home directed trips by person. The percentage of regular trips was found to be approximately 75% of all out-of-home trips.

Order of destinations

As a first step, it is shown how the individual hierarchy of important destinations might potentially change due to congestion charging. Table 29 represents how many places within the *regular repertoire of destinations* (see also above) are substituted by others in the pricing period. An average number equal or near zero would mean total stability of behaviour and no change between the respective periods at all. The analysis indicates that a substitution rate of about a third for the repertoires of most important destinations. Although this is a considerable change given the broad routinisation of spatio-temporal behaviour, the figures do not deviate considerably from the analysis of equivalent GPS data such Atlanta or Borlänge[28].

If one applies a *rank correlation* similar results can be found: The average Spearman Rho describing the monotonous connection between the two rank series "hierarchy of unique locations in the control and pricing periods" varies between 0.68 (high kilometrage) and 0.77 (cordon) which may not be described as a perfect rank correlation[29].

Table 29 Shifts in destination choice hierarchy: Average number of important destinations substituted (base: first N most important destinations without home)

Combination of pricing periods		First 5		First 10		First 20	
	N	Median	Mean (Std.)	Median	Mean (Std.)	Median	Mean (Std.)
Control – High	91	2	1.6 (1.0)	3	3.2 (1.3)	7	6.6 (2.6)
Control – Low	71	2	1.7 (0.9)	4	3.6 (1.5)	7	7.9 (3.2)
Control – Cordon	38	2	1.8 (1.0)	4	4.1 (1.8)	9	9.5 (3.5)

[28] The mean substitution rate for Atlanta – if for example considering two consecutive 12 weeks periods – is 2.1, 4.6 and 9.5 for the first five, ten or twenty most important destinations respectively.

[29] Spearman's rank correlation coefficient is a non-parametric measure of correlation – that is, it assesses how well an arbitrary monotonic function could describe the relationship between two variables. It does not require the assumption that the relationship between the variables is linear, nor does it require the variables to be measured on interval scales. It can be used for variables measured at the ordinal level. In principle, the coefficient is simply a special case of the Pearson product-moment coefficient in which the data are converted to ranks before calculating the coefficient. It may take values between -1 (perfect negative rank correlation) and 1 (perfect positive rank correlation)

Destinations by zones and crossing of zonal borders

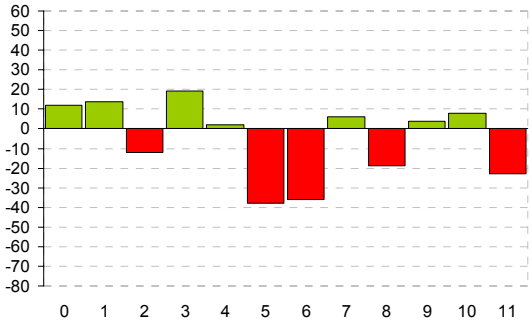
One of the likely changes of main interest for transport planning and policy is certainly the distribution of destinations by sub-region or zones. As the central parts of urban agglomerations are affected by congestion most severely, a relief from traffic for those areas is welcome. If pricing matters – as expected by transport policy –, destinations in the "more expensive" zones get less attractive to the driver if there are alternatives in the same or less expensive zones. This is especially true for cordon pricing; however, the same effect is possible for kilometrage pricing schemes where places further away from the current location get less desirable due to budget considerations.

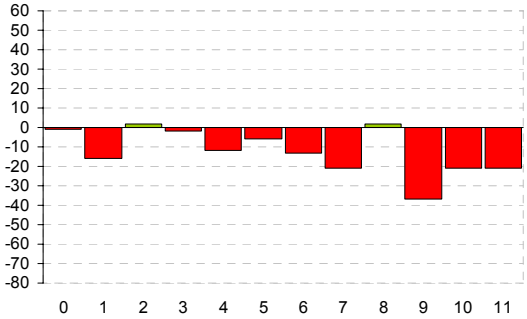
The results shown in Figure 39 provide a first impression of the change in the destination distribution. The chart provides an aggregate picture for non-regular travel which is presumably more sensitive to pricing as alternatives might be easier chosen. The figure represents the percentage change of trips and unique locations between the period of charging and the respective control period by zone (zonal structure in Figure 12).

Trends are especially visible for the cordon based pricing. The high kilometre pricing scheme shows an ambivalent picture without a tendency towards a reduction in the inner-city zones. What can be seen is a general reduction in travel for the pricing period. Some change towards avoiding more expensive zones is evident for the cordon based pricing. The pricing obviously causes reductions in the first ring around the city centre and in the city centre cordon itself (zones 8, 9, 10 and 11).

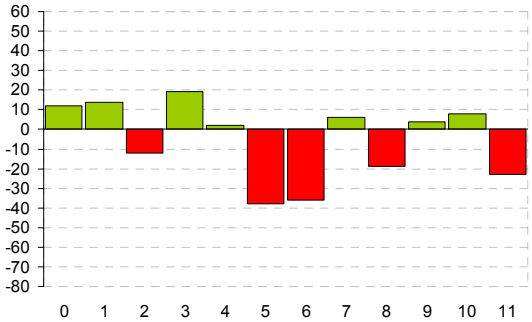
Figure 39 Percentage changes of amount of trips and locations in the different zones: "Non-regular" travel (comparison with control period)

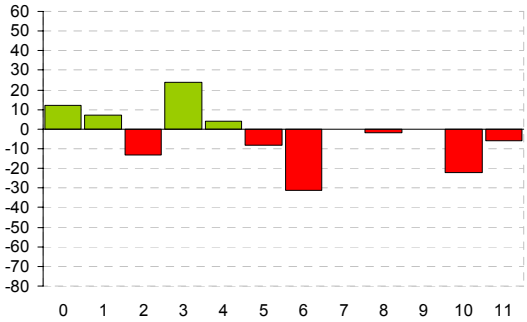
Trips	Locations
Control – High N = 4364/3888 trips	N = 2021/1843 locations



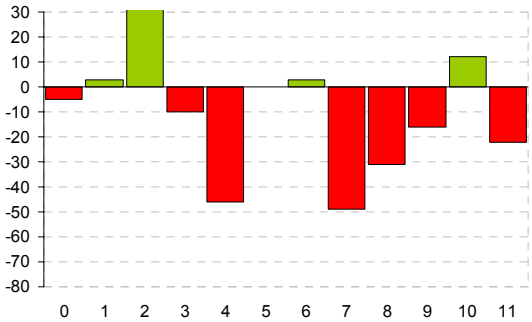


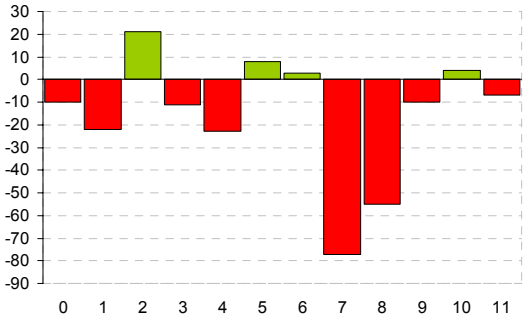
Control – Low N = 2672/2650 trips N = 1262/1284 locations





Control – Cord. N = 1205/1156 trips N = 580/528 locations





Note: Zone 0: out of pricing charging area

The analysis of destinations by zones leads to another question which was already touched above: Is the home zone a preferred destination if mobility pricing is introduced? Table 30 gives the percentage share of trips and destinations in the home zone of the respondents. Again, no clear trend is visible. The shares between the control period and the pricing are almost identical and do not deviate statistically.

Table 30 Share of trips and unique locations in the household location zone (global averages without trips to home location) [%] (Std.)

	Trips				Unique locations			
	All trips		Non-regular trips		All trips		Non-regular trips	
	Control	Pricing	Control	Pricing	Control	Pricing	Control	Pricing
Control – High (N=91)	39.7 (21.7)	39.2 (21.7)	42.9 (23.6)	42.9 (23.4)	33.8 (16.7)	33.9 (17.1)	37.9 (19.0)	38.6 (20.2)
Control – Low (N=71)	45.6 (22.8)	44.4 (24.2)	48.8 (25.3)	48.0 (25.9)	45.6 (22.0)	44.6 (21.9)	48.8 (24.0)	47.4 (23.2)
Control – Cordon (N=38)	38.1 (22.5)	38.5 (23.1)	42.4 (25.9)	44.4 (26.6)	34.5 (19.4)	35.6 (19.7)	38.2 (21.4)	41.2 (22.6)

Crossing zonal boundaries

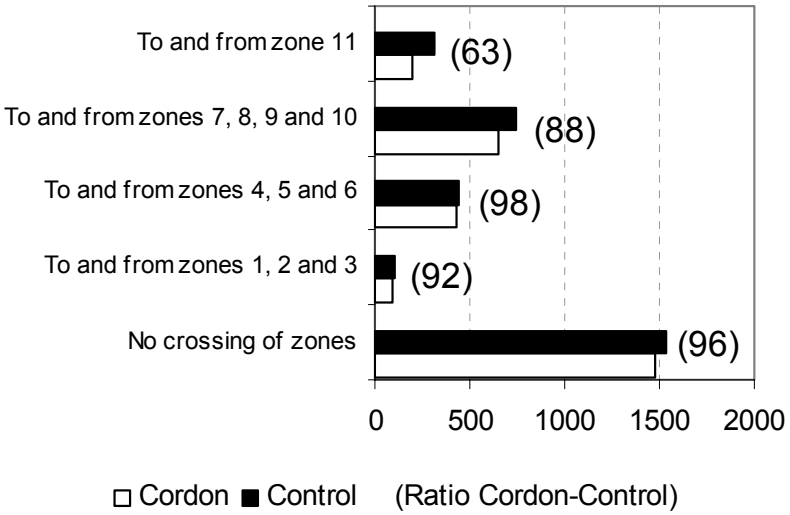
Apart from the distribution of destinations by zones, it is interesting to analyse if the number of trips entering or leaving zones – which is charged in the cordon based pricing scheme – is altering the respondents' travel behaviour. As crossing the zonal boundary is "punished" (leading to a deduction of the pre-paid amount of money), travellers eventually try to avoid choosing destinations which require crossing the cordon or a sub-zone within the cordon.

The following figure gives the total number of origin-destination relations by zones (or cordons which are constituted by single zones) and the ratio of these numbers for the control period to cordon based pricing. As one can easily see, most of the travel observed is inner-zonal with about 50% of origin – destination linkages in one zone.

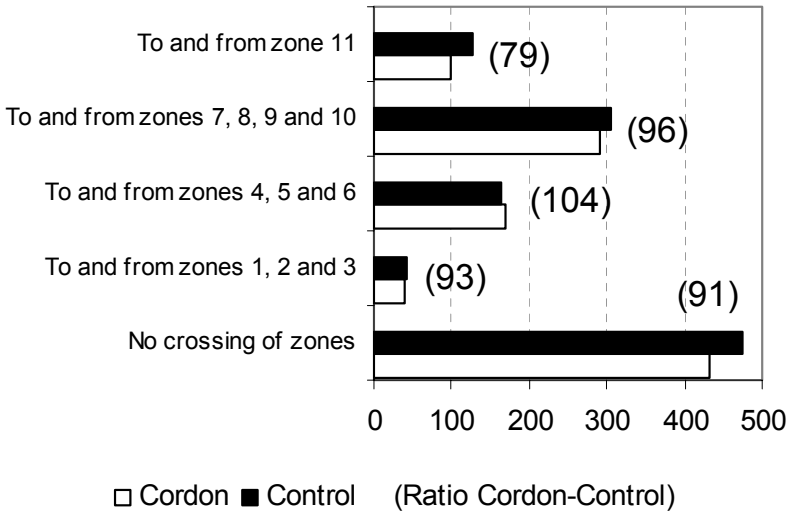
The interesting but certainly not unexpected result here is a behavioural change especially for the Copenhagen inner city cordon. This cordon consists of zones 7 to 11 with the oldest part of the town as well as the main shopping area in zone 11. The reduction between the pricing and the control period is considerable with about 20 to 30 percent in OD-relations. Slightly ambiguous is the fact that the reduction is less obvious for trips predefined as non-regular. For those trips the potential for choosing an alternative destination outside the expensive zones may be assumed to be greater. However, the results are not entirely clear assumingly due to the small sub-sample used here.

Figure 40 Amount and ratio [%] of O-D (D-O) relationships: Cordon based pricing compared to control period (totals)

All trips



"Non-regular" trips



Note: The term "crossing" does not capture the entering / leaving of several zones but only the origin – destination relation

The findings in general show that the cordon pricing might be successful for charging strategies which aim to reduce traffic and congestion locally – especially in the sensitive inner-city

areas. The results are in line with the real-life experiences made in cities such as London or Oslo where the inner-city areas are charged.

7.3 Summary of the enumeration results

The distribution of the number of trips and locations approaches a gamma distribution in the long term which is an interesting new finding given the typically observed left-skewed distribution in one or two day diaries is misleading for dynamic analyses.

The enumeration exercise has shown that the anchors of daily mobility are provided by a small number of regularly visited locations, which dominate the destination choice. It could be also shown that there seems to be a stable ratio of one unique location to four or five trips.

While the share of the most prominent locations is large, travellers do add new locations to their choice set regularly. The rates of innovation estimated here range from 0.2 to 1.5 in the long run. The contribution of leisure travel is considerable. Together with the steady rate of location innovation this indicates that variety seeking is a strong motivation for the travellers.

Few predominant locations form the core of locations clusters, but the number of identifiable clusters remain small; two or three for most travellers. Contrary to previous assumptions the work place is not such a prominent core. The share of clusters around workplace is low, even for full time workers.

In summary, the enumeration approach revealed a wide range of destination choice patterns between respondents of the same surveys and between the different surveys analysed. Whereas this could be expected given the individual differences of needs and preferences in time and space, a common trend could be identified which defines destination choice as a process where places are permanently re-used, discovered, taken stock and put aside.

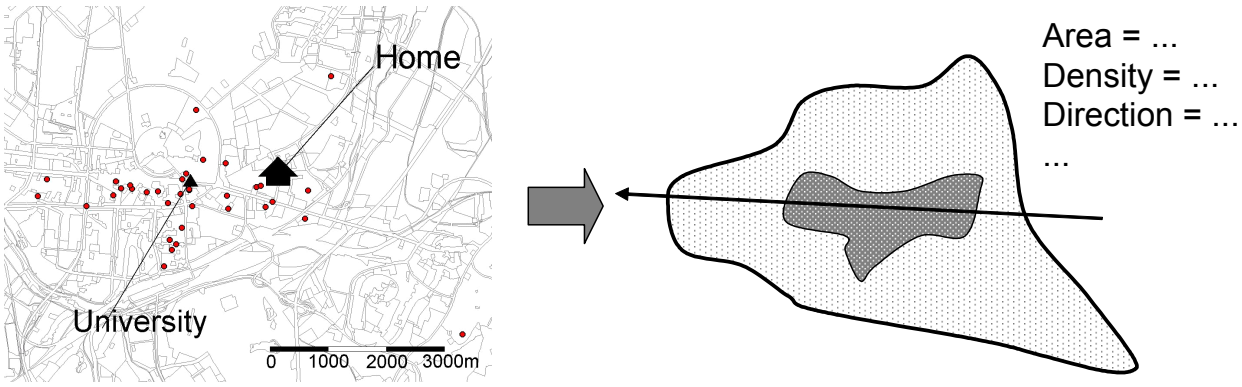
8 Continuous representation of urban space usage

The second approach of the analysis of human activity spaces focuses on a continuous representation of space. It essentially captures the transformation of point patterns - such as the spatial distribution of activity locations - into geometrical shapes (Figure 41). The transformation process will provide answers to the following questions:

- Given observed locational choices, which further locations are likely (probability of visit)?
- Which part of the region is used according to one's needs and preferences (density / intensity of usage)?
- When moving through nets, which adjacent area is perceived and possibly memorised (perception / memorising of infrastructure)?

In addition, these primary measures can be potentially used to define other measures, such as local density distributions or main direction (orientation) of the activity space.

Figure 41 Transforming activity point pattern into continuous space representation



8.1 Measures of continuous space usage – an introduction

The activity space measures essentially relate to descriptive and analytical concepts developed in *habitat research* in biology (animal movement studies) (Worton, 1987) as well as to approaches originated in *operation research* (Kruskal, 1956; Prim, 1957). Mathematically they may be grouped into *parametric* and *non-parametric* approaches: Parametric models are subject to mathematical features which force a predetermined shape on the geometry with implications for the interpretation of the result whereas non-parametric models have higher degrees of freedom to adopt the shapes observed.

Movement analysis in habitat research

The analysis of movement and time-use patterns as well as interactions of animals has been a focus in biology, in particular in zoological studies for some time. As in this approach which will deal with the locational choice of human beings, zoology uses longitudinal and spatially referenced data to define territories or so called *home ranges* of individual creatures. Suitable data is mostly collected by radio tracking or live trapping. The mapping and estimation of the size and structure of home ranges allows biologists to better understand behavioural and ecological phenomena.

The respective literature has long discussed suitable methods to visualise and calculate geometries which represent animal movement (see e.g. Worton, 1987; Thompson, Boer and Pianka, 1999; Southwood and Henderson, 2000). Figure 42 gives examples of geometries of frequently used approaches.

Worton (1987) groups the available home range methods into a set of classes which can be titled as

- polygons
- centre of activity studies
- nonparametric methods.

The polygon methodology consists of simple approaches which often connect the peripheral locations observed to establish the home range. Often a *minimum convex polygon* (MCP) is used which is the smallest area convex polygon capturing all points[30].

Whereas the polygon method only gives the extent of the animal's territory, centre of activity approaches and non-parametric approaches also yield the *intensity of usage* as a result. The intensity is connected to a key concept in home range analysis, which is the *utilisation distribution* (UD) function. It mathematically describes the concentration or dispersion of points within an area or – in general – the (territory) use pattern of animals (Samuel and Garton, 1985). It relates to a "(usually two-dimensional) relative frequency distribution of an animal's location over time" (Worton, 1987, 278) and is mostly represented as a bivariate model.

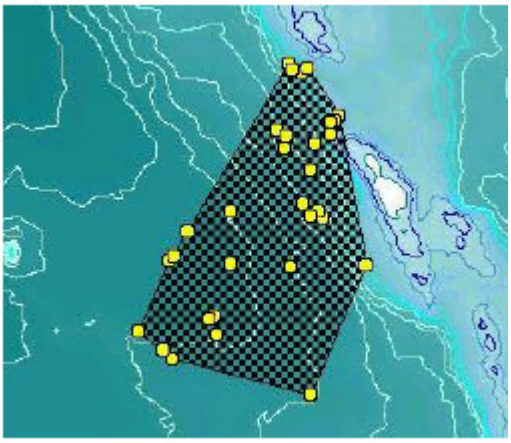
Centre-of-activity approaches define an arithmetic mean as a (mostly biologically meaningless) centre of the animal's home range and focus on the analysis of territory around this point. The extent of the space usage is often limited by a given geometrical shape, e.g. concentric rings, which define a fixed percentage confidence region based on the animal's utility distribution. Centre-of-activity approaches are therefore parametric, *predetermined* or *probabilistic* as it is necessary to define a distribution of intensity of use about the centre.

Finally, non-parametric methods evade the predefinition of distributional assumptions - such as the normal distribution for observed locations - which are obviously seldom met by the creatures' behaviour. Non-parametric methods are mainly based on an interpolation and/or a smoothing of the two dimensional locations. For the interpolation of observed locations, data is often represented in a grid cell form. One principle is that every cell containing an observation influences its neighbouring cells by some contiguity rules which leads to an illustrative representation of movement directions and eventual biases (see Voigt and Tinline, 1980). A smoothing of point data may be obtained by several approaches such as a Fourier transformation (Anderson, 1982), a harmonic means method (Dixon and Chapman, 1980) or kernel density estimation (see below). The application and visualisation of non-parametric methods have particularly benefited from the development of advanced GIS technology over the last 20 years.

[30] The MCP or "convex hull" has been recently used by Buliung and Kanaroglou (2004) to visualise activity-travel behaviour, too.

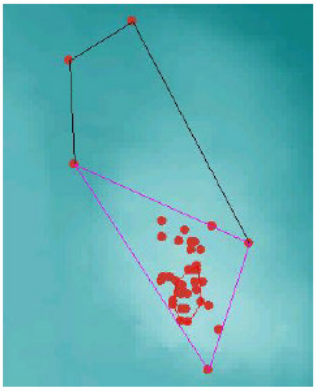
Figure 42 Measuring home ranges: Often used approaches

Minimum convex polygon (MCP)
(e.g. Mohr, 1947)



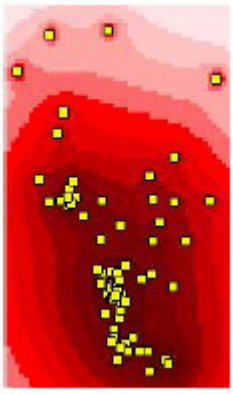
- Non-probabilistic
- Peripheral locations define geometry
- Does not give the probability of usage
- Size of geometry dependent on sample size
- Comparison of sizes requires standardisation of sampling
- No estimation of variance

Percent convex polygon (PCP) or MCP reduced by outliers (e.g. Michener 1979)



- Boundaries cover only a specified innermost percentage of all observations
- Reduces outlier effects
- Removing of outermost observations may be based on different algorithms (e.g. deleting observations farthest away from mean, re-calculation of mean and so on)

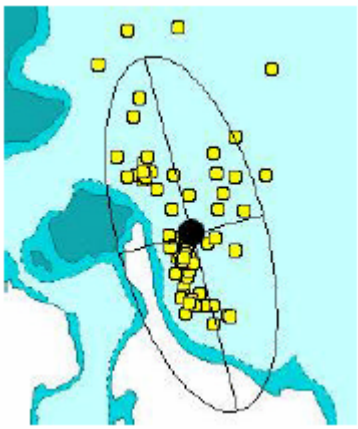
Harmonic mean home range (e.g. Dixon and Chapman, 1980)



- Non-parametric method based on the volume under a fitted three-dimensional UD
- Defined percentage of the harmonic mean contours
- Contours may be chosen as harmonic mean values or as specified percentages of animal's UD
- Preferably based on a uniform distribution
- (Minimum value of the non-parametric harmonic mean distribution)

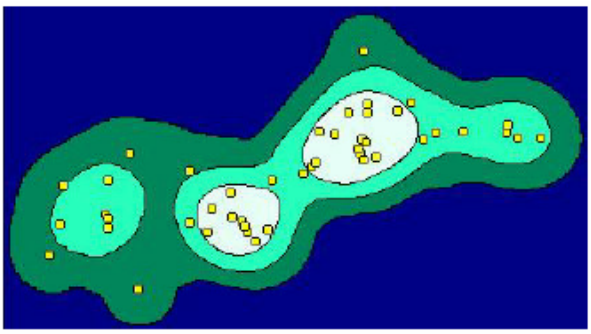
cont.

Jennrich-Turner home range
(Jennrich and Turner, 1969)



- Parametric
- Confidence region around mean of a two-dimensional bivariate normal distribution
- Actually only applicable to normally distributed data
- (for a comprehensive description of the concept see 8.2)

Kernel home range
(for an application see Kirkby, 2001; for basics see Silverman, 1986)



- Non-parametric; without requiring assumptions on distributional form of underlying point patterns
- As sample points may be thought to have a probability distribution associated with each of them, points may visualised with a density function over it
- Mixture of distributions yields estimates for probability density function
- Well understood theoretical features (for a comprehensive description of the concept see Chapter 8.2)

Source: Hooge and Eichenlaub (1997) (pictures); Worton (1987)

8.2 Measures applied

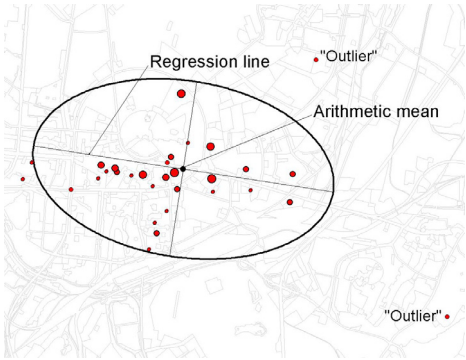
The methodological development to capture human activity spaces has lead to three measures which are models of human behaviour and simplifications of environmental perception and actual decision processes (see Schönfelder and Axhausen, 2002; 2003a; b). The concepts are:

- a two-dimensional confidence ellipse or standard deviational ellipse similar to the Jennrich-Turner home range (see above)
- activity space measured based on *kernel densities*
- the measurement by *shortest paths networks* linking all destinations visited conceptually similar to *Minimum Spanning Trees*

Figure 43 gives an introductory overview of the measures which are described in detail in the following.

Figure 43 Measuring activity spaces: Overview of concepts developed

a) Confidence ellipses



Dots show location and frequency of visit

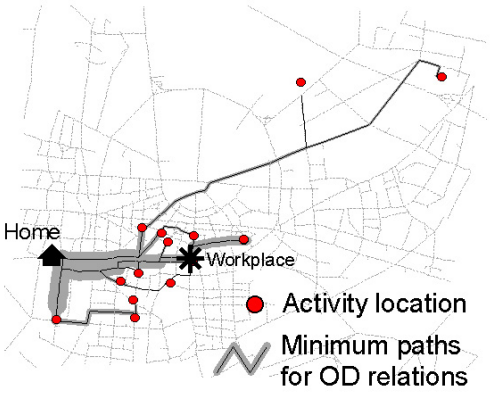
- Basic approach: Confidence ellipses, i.e. smallest possible area in which a defined share of all visited locations is situated
- Measure: Size (plus direction of main axis)
- Special feature/quality: Shows dispersion of visited locations

b) Kernel densities

Dots show location and frequency of visit

- Basic approach: Density surface; based on the proximity of activity locations
- Measures: a) Area covered exceeding a certain threshold value, b) "Volume" (sum of all kernel densities calculated)
- Special feature/quality: Represents local clusters / sub-centres within individual activity space

c) Shortest paths network (SPN)



Boldness of links corresponds to frequency of usage

- Basic approach: Set of shortest paths between all origin-destination relations observed
- Measure: a) Length of tree (unweighted/weighted by frequency of single link usage), b) Size of buffered area around the tree indicating potential knowledge spaces
- Special feature/quality: Indicator for the perception of urban space and networks

Confidence ellipses

Confidence ellipses – also called prediction interval ellipses – are an explorative method to investigate the relationship between two variables (bivariate analysis). They are often used for hypotheses testing and to detect outliers. Confidence ellipses are analogous to the confidence interval of univariate distributions defined as the smallest possible (sub-)area in which the true value of the population should be found with a certain probability (e.g. 95%). Similar methodological techniques have already used in the activity space oriented work of the late 1970s UMOT project as briefly introduced in Chapter 3.7 (Zahavi, 1979; Beckmann, Golob and Zahavi, 1983a; 1983b).

In human geography the original concept of the confidence ellipse as described in the following has not been applied to travel data as such – however the approach was used to analyse social interaction based on activity frequency or density data (Hyland, 1970; Buttimer, 1972; Herbert and Raine, 1976). Raine (1978) for example describes the application of the standard deviational ellipse approach to retrospective activity frequency data of a small sample of residents form Cardiff. His study focuses on the different spheres of activities (e.g. friendship, service and joint) within a limited residential area and its main spatial opportunities[31]. It could be found that the single ellipses intersect considerably which shows that movements to particular places reflect and even initiate other patterns of interaction.

Turning to the details of the concept, the size of the ellipse area represents the actual measure for the activity space size. It may be used to compare the dispersion of the activity space between travellers or between subperiods of observation for one single respondent (see Figure 44 for an example).

In order to obtain a more realistic representation of human behaviour, modifications of the basic concept are made. The travellers' home location is taken as a substitute for the mathematical centre (i.e. the arithmetic mean point) in the calculation of the covariance matrix. This stresses the importance of home for daily life travel and would use a real-world location instead of the artificial mean point of the chosen locations.

The calculation of the ellipses is tied to the assumption that the variables are bivariate-normal. This was shown to be true for the activity locations of travellers (Moore, 1970).

[31] The places were pre-specified by the research team which is a fundamentally different approach compared to a longitudinal travel diary survey or a GPS observation which capture actually visited locations.

The ellipses are computed with the covariance matrix of all points (activity locations) of a person

$$S = \begin{pmatrix} s_{xx} & s_{xy} \\ s_{yx} & s_{yy} \end{pmatrix} \tag{23}$$

where each covariance is defined as

$$s_{xx} = \frac{1}{n-2}\sum_{i=1}^{n}(x_i - \bar{x} / HomeX)^2 \tag{24}$$

$$s_{yy} = \frac{1}{n-2}\sum_{i=1}^{n}(y_i - \bar{y} / HomeY)^2 \tag{25}$$

$$s_{xy} = s_{yx} = \frac{1}{n-2}\sum_{i=1}^{n}(x_i - \bar{x} / HomeX)(y_i - \bar{y} / HomeY) \tag{26}$$

The determinant of the covariance matrix (generalised variance) is

$$|S| = s_{xx}s_{yy} - s_{xy}^2 \tag{27}$$

with the ellipse size A

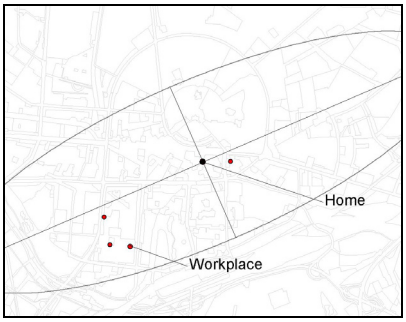
$$A = 6\pi|S|^{\frac{1}{2}} \tag{28}$$

The orientation of the ellipse is determined by the sign of the linear correlation coefficient between the coordinates x and y of the activity locations; the longer axis of the ellipse (if shown) is the regression line.

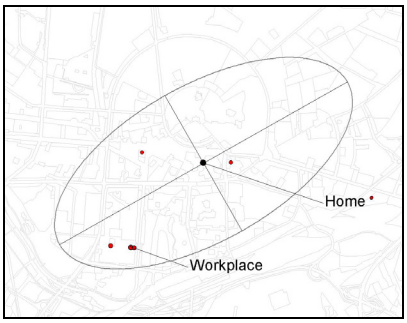
Figure 44 Activity spaces over time by 95% confidence ellipses

Mondays

Tuesdays



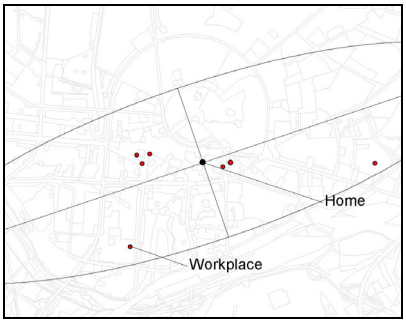
Wednesdays



Thursdays

Fridays

Saturdays

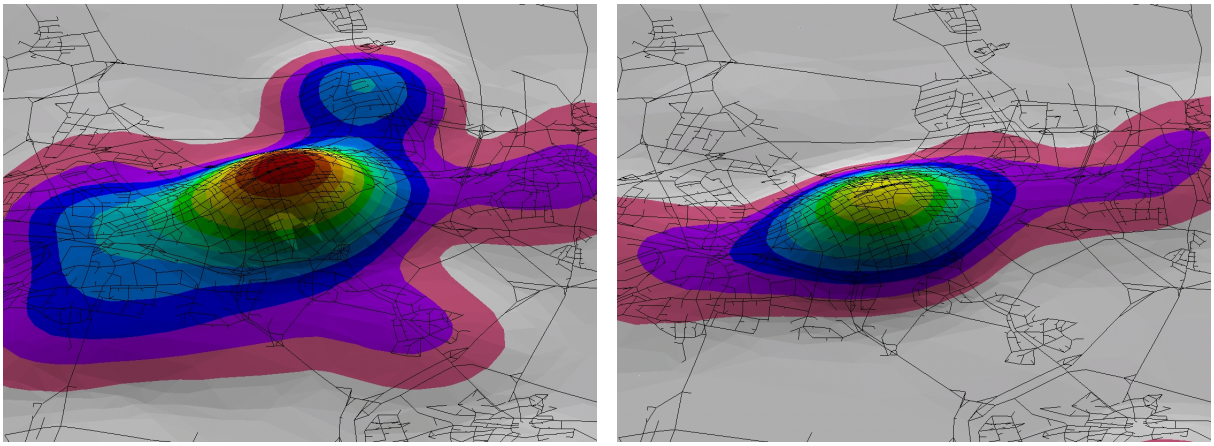


Note: graph shows one single Mobi*drive* respondent (female, 33, nurse, 2-person household); same clipping of underlying urban area; centre represented by household's home location;

Kernel densities

Kernel densities have been already applied successfully to large cross-sectional data sets (Kwan, 2000; Buliung, 2001). Modern GIS applications include tools to calculate such density measures effectively, including 3D visualisations which impressively show space-time interactions (Figure 45).

Figure 45 Aggregate activity density patterns



Note: Mobi*drive*: Total Karlsruhe sub-sample; Left: leisure activities, right: work

The approach applied here is related to those studies but is focusing on individual densities. In this case, the intensity corresponds to the dispersion or clustering of places visited and can be complemented by the level of activity performance, i.e. the frequency of visit at the observed locations.

The technical implementation of the visualisation and the measuring of the densities employs a Geographical Information System (GIS). GIS applications usually provide special modules for density calculation. ARCINFO® (which is used in this study along with its sister product ARCVIEW®), for example, estimates densities within its integrated GRID module where raster grids such as shown in Figure 46 are divided into a definable amount of cells. Finally, the density values are assigned to the cells according to the kernel densities estimated for the underlying point pattern.

Figure 46 Example for density surfaces represented by grid structures

Sources: Fotheringham, Brunsdon and Charlton (2000) 193; Tschopp, Fröhlich and Axhausen (2006) 8 (rail accessibility for Switzerland 1950)

The basic process behind the estimation of kernel densities is a transformation of a point pattern (such as the set of activity locations visited) into a continuous representation of density in a wider area (see Silverman, 1986 or Fotheringham, Brunsdon and Charlton, 2000). Generally speaking, the estimation is an interpolation or smoothing technique which generalises events or points to the area they are found in. The interpolation then leads to a calculation of a value for any point, cell or sub-region of the entire area which characterises the density.

Probably the most common approach, implemented in several GIS packages, is the *fixed kernel method* (also applied here). Similar to histogram techniques, a symmetrical – variably distributed – *kernel function* is placed over each data point. For all locations in the entire area ($\mathfrak{R}$) – not only for the data points – the overlapping values are summed which yields the density or intensity estimate (Figure 47). This automatically leads to a smoothing of the surface where the level of smoothness depends on the *bandwidth* of the kernel function which is analogous to the width of ordinary histogram boxes. The bandwidths may be varied according to the necessary degree of smoothness – with greater smoothing at bigger bandwidths or values of the smoothing parameter. The GIS finally may represent the resulting estimates for all grid cells as a continuous surface.

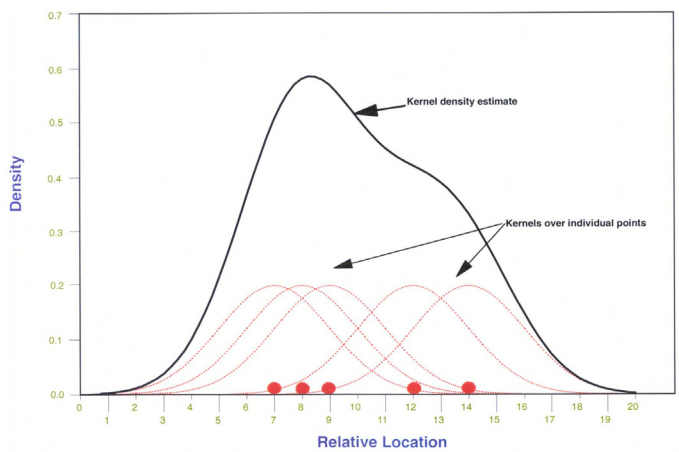
Considering a grid structure in which single points are substituted by grid cells, the base kernel density is given by the formula:

$$\lambda(s) = \sum_{d_i < \tau} K\left(\frac{d_i}{\tau}\right) \tag{29}$$

With

- λ density estimate at grid point s
- T bandwidth or smoothing parameter
- K kernel function (to be further specified)
- d_i distance between grid point s and the observation of the ith event

Figure 47 Kernel density estimates



Source: Adopted from Ned Levine and Associates (1999) 202

The kernel function K itself may have different forms such as normal, triangular or quartic. The results do not differ significantly as long as the distribution is symmetrical. In the following, a quartic kernel function – implemented by default in ARCINFO (see Mitchell, 1999 for details) – is used which leads to the following kernel density

$$\lambda(s) = \sum_{d_i < \tau} K\left\{[\frac{3}{\tau^2 \pi}][1 - \frac{d_i^2}{\tau^2}]^2\right\} \tag{30}$$

A particularity of the quartic function – e.g. compared to a normal distribution – is that outside the specified bandwidth τ, the function is per definition set to zero – with implications for the behavioural model. This means that activity locations outside a specified radius do not contribute to the density estimation of the particular point (cell) in space. In other words, a quartic distribution of the kernel function adds weight to locations closer to the centre of the bandwidth than those further apart (see NedLevine and Associates, 1999 for characteristics of the different kernel forms).

The actual activity space measures are defined by the number cells which exceed a given density threshold and the sum of all grid cell density values (i.e. the *volume*).

Figure 48 shows a visualisation of kernel densities for one Borlänge test driver. The observation period covers approximately 4 months. It shows nicely the variation in size and structure of the locational choice patterns over the week with a large activity space during the weekdays, similar densities for weekdays and Saturdays in the city centre area and around the home location as well as the reduced local travel intensity on Sundays.

Figure 48 Visualisation example (Borlänge GPS data) : Activity space compared by days of the week

Note: Graph shows activity spaces of a male retiree, 71years; observation period: app. 4 months; grid cell size: 500*500 meters, activity locations weighted by frequency of visit, bandwidth: 1000 m

Shortest paths networks (SPN)

By introducing a last measure for human activity spaces, it shall be acknowledged that transport network structures shape the travellers' perception of potential activity locations as well as the knowledge of place and the spatial orientation (Golledge, 1999). Hence, calculating the size as well as visualising the shape of human activity spaces should be oriented towards the paths chosen by the travellers.

One possibility to consider the network supply-travel interactions is to identify the part of the network which was actually used by travellers during the reporting period. This particular portion and the roads' adjacent built environment can be assumed to be known by the traveller. These *shortest paths networks* (SPN) are constructed by analysing the calculated shortest paths between all reported origin-destination pairs.

The concept is modelled on approaches such as *minimum spanning trees*: Within the framework of graph theory, Kruskal (1956), Prim (1957), Dijkstra (1959) and others developed algorithms that find minimum spanning trees for a connected and undirected graph weighted by edges. This means they find a subset of the edges that forms a tree that includes every vertex, where the total weight of all the edges in the tree is minimized. If the graph is not entirely connected, a minimum spanning forest (a minimum spanning tree for each connected component) is generated. The fundamental principle of the algorithms is as follows: It starts with a trivial graph *T* which is an arbitrarily chosen node of a network. In every following step, an edge with a minimum weight is searched which connects a further edge with the node. This edge and the respective node are added to *T*. The step is repeated as often as all existing nodes are added to T – which becomes a minimum spanning tree, finally.

The differences of the approaches may be described in brief as follows: In Kruskal's algorithm all nodes are existent at the beginning. The graph is a geometry of separated components which are interconnected step by step by adding further edges. In contrast, in Prim's approach the graph is connected in each iteration which is extended until the whole graph is spanned. The difference of Prim's algorithm compared to Dijkstra is the fact that the node (of an adjacent edge) which is not yet part of the tree needs to be as close as possible to any (!) of the existing Prim tree whereas Dijkstra considers the distance to the starting node. The latter approach therefore focuses on the total cost of then shortest path from the starting node to the node to be added.

SPN are an approximation of actual spatial decision making, only, as route choice information is not available for the travel diary data sets used[32]. As the route choice algorithm we chose the default Dijkstra procedure implemented in the ARCINFO® NETWORK module[33].

[32] A digitalised road network was only available for the City of Karlsruhe and the town of Borlänge at the time of analysis.

[33] Enhancements of this procedure are imaginable, e.g. by substituting the deterministic shortest path algorithm by a probabilistic one (see Sheffi, 1985; Bovy, 1996). Furthermore, the paths chosen can be properly assigned to the different modal networks according to the modes actually chosen for the different trips.

The structure and size of the network may be also interpreted as a quantitative indicator for the perception, knowledge and especially the usage of urban space. Considering the perception of the (built) environment, it can be assumed that there is considerable correlation between the frequency of using a network link and the knowledge of the surrounding area. It is widely agreed by psychologists and geographers that travelling through an environment is the common way of spatial learning and acquiring spatial expertise (Golledge, 1999).

What can be especially seen from the first of the two examples in Figure 49 is that the home location is the *major hub* for daily travel acting as a central node in the given road network. This is what could be expected as the share of complex trip chains with diffuse travel relations is much smaller than the amount of simple home-based trips, such as home-work-home, home-shop-home or home-leisure-home. For example, more than 70% of all Mobi*drive* home based activity chains (i.e. *tours* or *journeys*) involve only one out-of-home activity.

Figure 49 Visualisation examples of *shortest path networks* (Mobi*drive*)

Note: width of network links indicates frequency of usage

8.3 Analyses

The presentation of the results of the continuous representation of activity spaces follows the order of concepts in Chapter 8.2: *confidence ellipses*, *kernel densities* and *shortest paths net-*

works. The results will be related to each other as well as to selected results of the enumeration exercise in order to reveal fundamental relationships.

Confidence ellipses

The pattern of activity space sizes for all surveys follows a common trend[34] (Table 31 and Figure 50). In contrast to the number of trips and locations, the distribution is strongly left skewed. This is in principle true for both types of the surveys, i.e. the travel diary data including all modes and purposes as well as the car based GPS observations. Hence, a small group of travellers show a very large dispersion of their activity patterns whereas the majority of respondents' activity space area is below average (median < mean).

[34] As the surveys originate from different spatial reference frames, the comparative analysis of the confidence ellipses will be often limited to „local trips" where this appears necessary. The definition of local trips is: Mobi*drive*, Thurgau, Uppsala and Copenhagen: Trips not further than 20 km from home location; Borlänge: all trips as monitoring was limited to the town of Borlänge and surrounding area (20 km radius around the centre of town). Clearly, this ad-hoc approach constrains the maximum size of the geometries (max. 1.600 km2), which can be accepted though for comparative purposes.

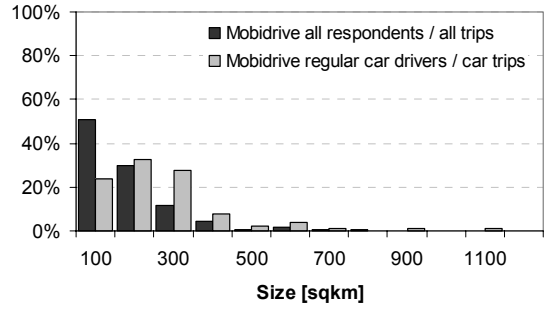
Table 31 Distribution of activity space sizes measured by confidence ellipses

		Ellipse size* [km^2]				For comparison: All trips
Survey	N	Mean	Std.	Median	Skewness	Median
Mobi*drive* all respondents /all trips	316	133	122	99	2.3	850
Car trips only	173	200	173	151	2.0	711
Car trips of regular car drivers**	99	212	169	177	2.3	1009
Thurgau all respondents /all trips	229	267	255	176	1.3	1263
Car trips only	152	342	286	278	0.9	850
Car trips of regular car drivers**	102	382	297	311	0.7	987
Uppsala all respondents /all trips	144	54	65	31	3.3	225
Car trips only	65	104	114	64	2.2	493
Car trips of regular car drivers**	32	94	112	69	3.5	643
Borlänge car trips	66	244	170	188	1.5	188
Copenhagen car trips (control period)	198	161	107	133	1.4	780

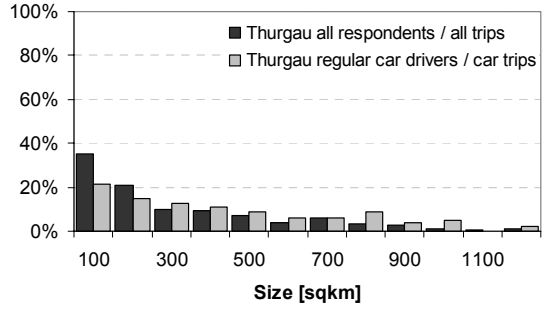
* 95% confidence ellipse based on local out of home trips; centroid = home location
** Regular car driver: Share of car trips (driving) exceed 50% of all trips made

Figure 50 Distribution of activity space sizes measured by confidence ellipses: Histogrammes

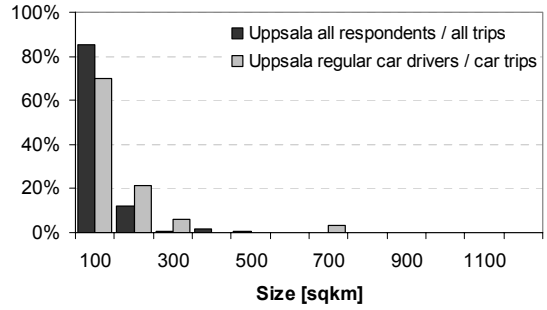
Mobi*drive*



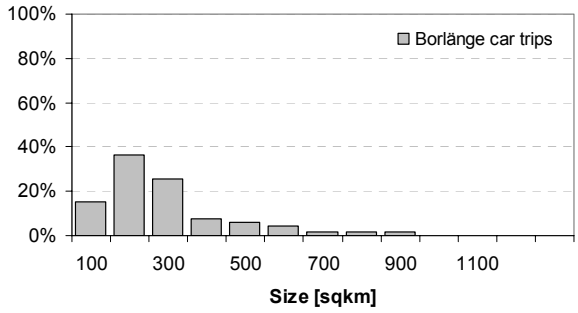
Thurgau



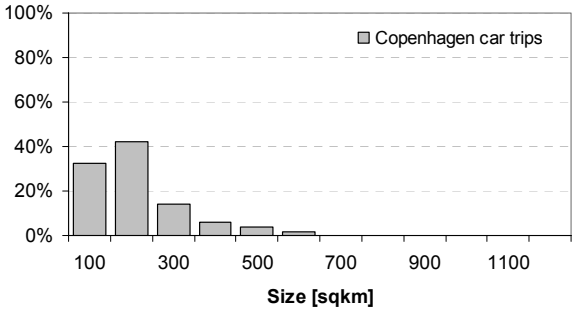
Uppsala



Borlänge



Copenhagen

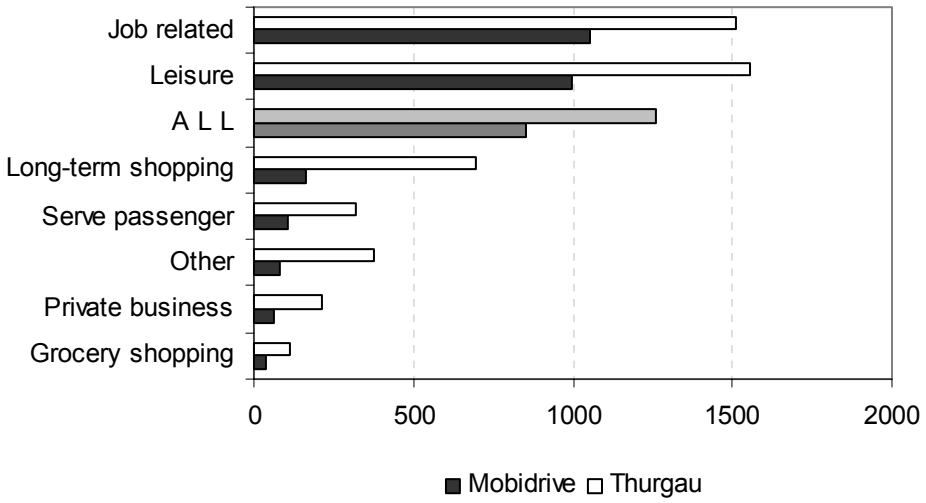


Note: 95% confidence ellipse based on local out of home trips; centroid = home location

If the activity spaces are categorised or filtered by trip purpose, an interesting picture emerges: The medians for job related and leisure are far above the overall median which shows the great dispersion of places visited for those purposes. Hence, especially leisure with its large share of trips contributes heavily to the total dispersion of places and therefore to the overall size of the activity space. Shopping and private business locations which are visited

also with a great regularity are found to be distributed much closer to the assumed centroid of daily life, i.e. home. Similar results yielded the analysis of the activity clustering (see above). It should be noted though that the expressiveness of Figure 51 has its limitations: The values for work and school are dropped as the ellipses can not be calculated if only one location is identified. This is especially critical in the case of Thurgau as a rural region where many respondents have their workplace in the Zurich area which might be 50 km away from the home location.

Figure 51 Median confidence ellipse size by purpose: Mobi*drive* and Thurgau



Note: All (!) out of home trips; 95% confidence ellipse; centroid = home location

Investigating the impact of a first set of determinants on the shown distributions (Table 32), no clear picture emerges. Nevertheless, a few trends can already be made out: First, the size of the activity space grows with the usage (availability) of a car. Regular drivers show higher means for the ellipse sizes than the overall sample average. This could have been expected and will be confirmed in the concluding analysis of variance. Second, the clustering of activities in groups of nearby locations as analysed in the enumeration section above has a slightly negative impact on the size of the activity space. This was expected, too, as the confidence ellipse is by nature a measure of dispersion. The finding is true for the all-mode analysis for Mobi*drive* and Thurgau data with correlations of –0.1 between the ellipse size and the cumulative share of trips to the five most important locations. Finally, it is interesting that a signifi-

cant negative correlation between the number of trips and the ellipse size could be found for the GPS observations (similar however non-significant trends are observable for all other surveys and groups). The spatial concentration of the activity patterns obviously increases with the length of the observation period which reflects by some means the dominance of the few important poles of daily travel, such as daily grocery, workplace or school. This again confirms the finding of the enumeration exercise which has already indicated the same tendency (see above). However, the resulting correlations are relatively weak which illustrates the ambiguity between concentration and a permanent (moderate) extension of the traveller's activity space – even though novel places never or only slowly obtain the same importance as locations belonging to the standard activity space repertoire.

Table 32 Confidence ellipses: Basic characteristics and correlation with the amount of travel

		Correlations*		
	N	N trips	N locations	Concentration of trips in 5 locations**
Mobi*drive* all respondents /all trips	316	-	-	-0.1
Car only	173	-	-	-
Car trips of regular car drivers	99	-	-	-
Thurgau all respondents /all trips	229	-	-	-0.1
Car only	152	-	0.2	-
Car trips of regular car drivers	102	-	-	-
Uppsala all respondents /all trips	144	-	-	-
Car only	65	-	-	-
Car trips of regular car drivers	32	-	-	-
Borlänge	66	-0.4	-	-0.4
Copenhagen (control period)	198	-0.2	-	-

Note: 95% confidence ellipse based on local out of home trips; centroid = home location
* (Pearson) Correlations shown are significant at the 0.05 level (2-tailed)
** Cumulative share of trips to the five most important locations

One of advantages of the multi-months GPS observations is the possibility to compare the size of the activity spaces over longer periods. The stability of activity spaces was already analysed for Mobi*drive* (Srivastava and Schönfelder, 2003) but with no definite results for long-term stability. This was mainly due to the limited length of the reporting period which does not allow to define sufficiently long continuous sub-periods.

For the Borlänge and the Copenhagen data set this is possible. As a straightforward analysis approach, the monitoring period was divided into (non-overlapping) three-weeks intervals for

which sizes of the confidence ellipse were calculated. A period of two to three weeks could be identified in the Mobi*drive* studies earlier as duration of relative stability for temporal phenomena of travel behaviour (Schlich and Axhausen, 2003).

The investigation of the similarity of two consecutive sub-periods shows that there is a remarkable degree of stability. On average, the indicators number of trips, number of unique locations and size of the activity space of two successive periods of a test driver correlate considerably with each other – up to 0.65 (Table 33).

Table 33 Correlation coefficients between selected activity space characteristics of two consecutive sub-periods (3 weeks)

			"Last period"		
			Number of trips	Number of unique locations	95% confidence ellipse, local trips
"This period"	Number of trips	Borlänge	0.68		
		Copenhagen	0.60		
	Number of unique locations	Borlänge		0.62	
		Copenhagen		0.57	
	95% confidence ellipse, local trips	Borlänge			0.47
		Copenhagen			0.65
N (sub-periods of monitoring)		Borlänge	862	862	862
		Copenhagen	451	451	451

Note: (Pearson) Correlations shown are significant at the 0.05 level (2-tailed).

Kernel densities

Figure 52 illustrates the basic enumeration and calculation concept for the kernel density measures. For the first measure (i.e. *number of cells* or *area covered*), the number of shaded cells which exceed a given density threshold (here: 0) are counted and – if necessary – multiplied by the chosen cell size. This yields the area which travellers presumably perceive, know or even use.

The second main measure is the sum of all grid cell values (here: 23) which can be interpreted as the *volume* of a three-dimensional surface representation as in (see Figure 45 for an exemplary representation).

Figure 52 Enumeration and calculation of activity densities

0	2	3	2
0	7	0.9	0
1	0.1	6	1

Cell size: (e.g.) 500m X 500m

Number of non-zero cells: 9

Volume: 23

Total area with cells exceeding threshold 0: 2.250.000m^2 = 56% of the entire analysis area

For the comparison of the density measures, we chose the following parameters for the kernel estimation and evaluation:

- Point pattern base: unique locations weighted by frequency of visit
- Grid cell size: 500m X 500m
- Bandwidth of kernel function (search radius): 1000m
- Threshold value for the *area covered* measure: all cells with kernel density greater than 0

In order to obtain a better comparability for the different surveys, again the investigation area was restricted to a similarly large size. For technical reasons, the search area was defined to be a square of 20 by 20 kilometres around the respective centre of the survey region (instead of a circle around the travellers' home locations as for the ellipses). In average, this reduced the locations to be analysed by about 10-20% which can accepted.

The distribution of the first measure again follows a gamma distribution likewise the distribution of the number of trips shown above (Figure 53 and Table 34). Due to the different lengths of the observation periods, the mean differs considerably between the travel diary data sets and the GPS observations - which is already an indication that the measures depend on the amount of mobility observed. The Borlänge data shows the highest cell number and density

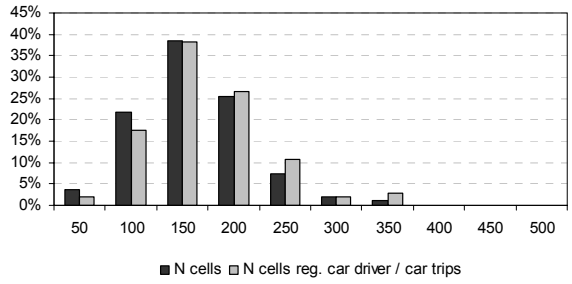
means which was to be expected due to extremely long monitoring periods – for some vehicles with up to 14 months. This gets especially obvious for the second sum of kernel densities measure (Figure 54) where the mean for Borlänge is seven to ten times higher than for the 5/6-week travel diary data.

Table 34 Distribution of activity space sizes measured by kernel densities

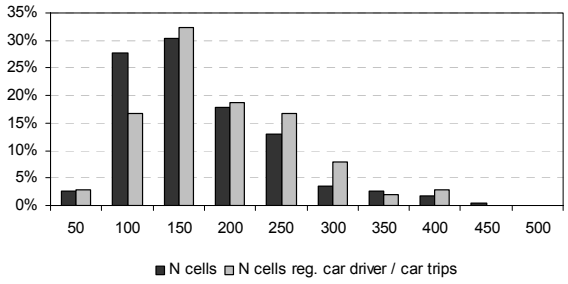
Survey	N cells					Volume				
	N	Mean	Std.	Median	Skewness	N	Mean	Std.	Median	Skewness
Mobi*drive* all respondents /all trips	317	137	54	132	0.7	317	55	21	54	0.5
Car trips of regular car drivers	102	148	58	136	0.9	102	43	17	42	0.4
Thurgau all respondents /all trips	230	147	73	134	1.1	230	57	23	54	0.6
Car trips of regular car drivers	102	162	74	145	0.9	102	46	20	45	0.6
Uppsala all respondents /all trips	144	86	28	80	0.5	144	47	23	42	1.0
Car trips of regular car drivers	33	95	29	95	0.1	33	37	19	35	1.1
Borlänge	66	325	103	329	0.2	66	365	242	338	0.9
Copenhagen (control period)	199	256	92	248	0.4	199	89	54	82	1.0

Figure 53 Distribution of activity space sizes measured by kernel densities: Cells with positive kernel densities – Distribution

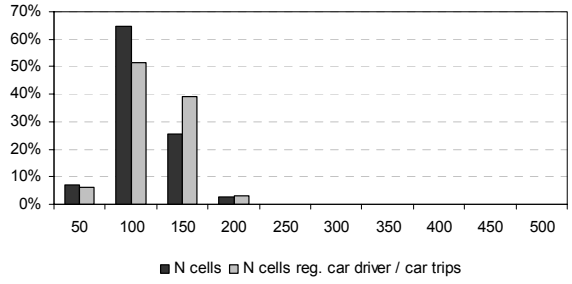
Mobi*drive*



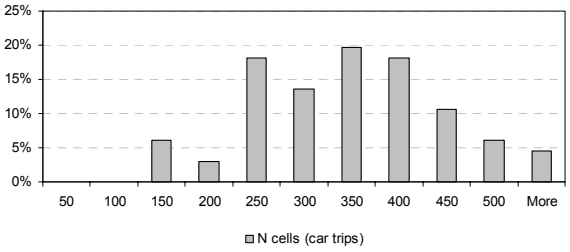
Thurgau



Uppsala



Borlänge



Copenhagen (control period)

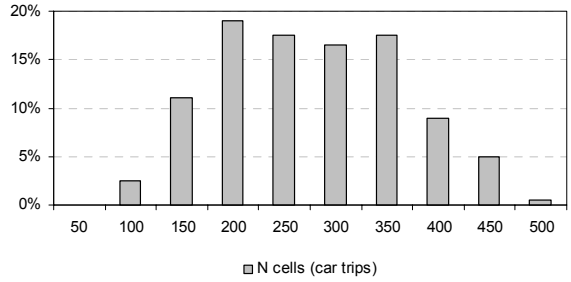
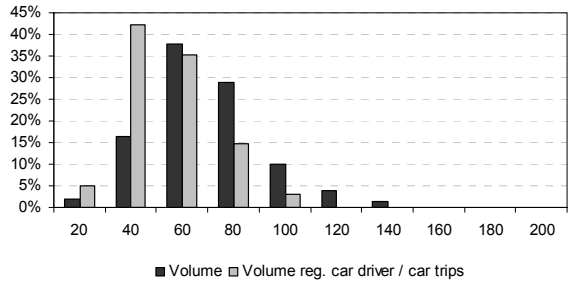
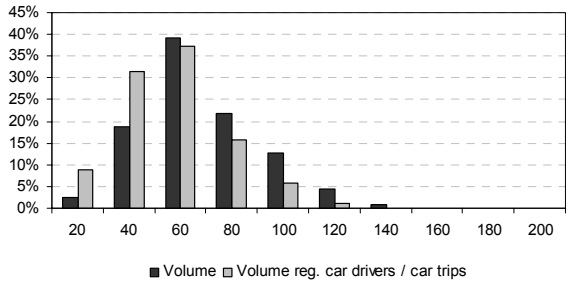


Figure 54 Distribution of activity space sizes measured by kernel densities: Sum of kernel densities (*volumes*) – Distribution

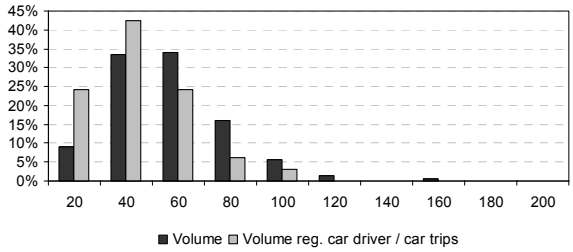
Mobi*drive*



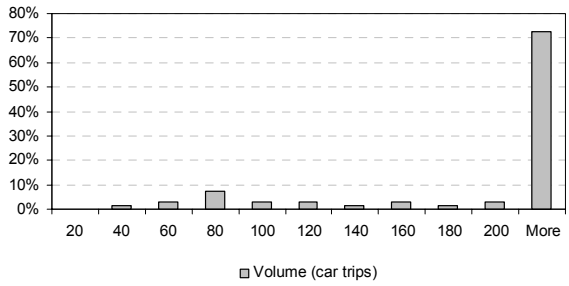
Thurgau



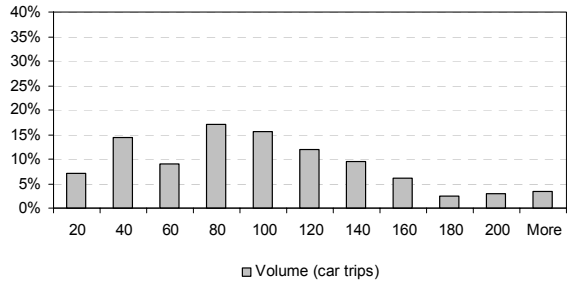
Uppsala



Borlänge



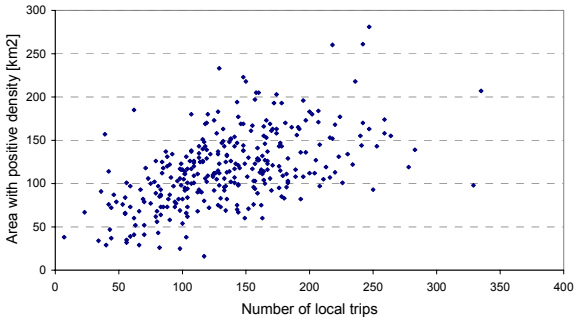
Copenhagen (control period)

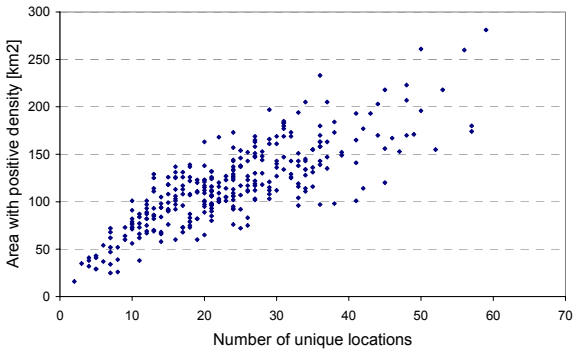


One of the interesting questions is, if the number of trips is a proxy for the size of the activity space. Figure 55 relates the kernel density measures to the number of trips, number of unique locations, days and finally to each other. The strength of the link between the number of trips, the number of unique locations, days and the size of the activity space are tight. The underlying (significant) correlations are between 0.6 and 0.8 which is a stronger relationship than the linkage between the confidence ellipse size and the number of trips/locations (Table 32).

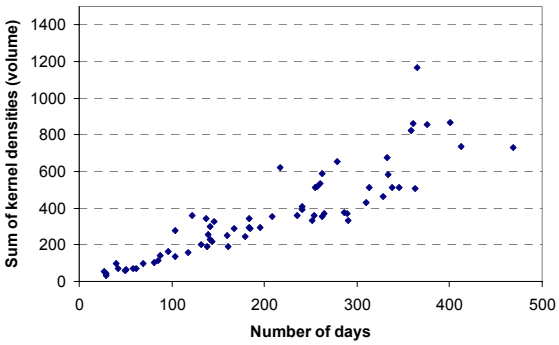
Figure 55 Activity space represented by kernel densities: Measures versus number of trips, number of unique locations visited and number of days as well as against each other

Area with positive kernel density (locations not weighted by number of trips) (Mobi*drive*; local trips only) [km^2]

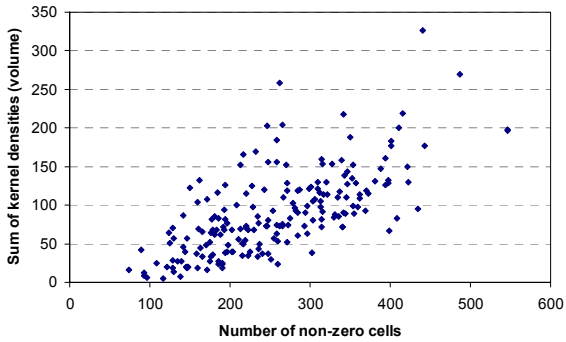




Summed kernel densities (volumes) (Borlänge)



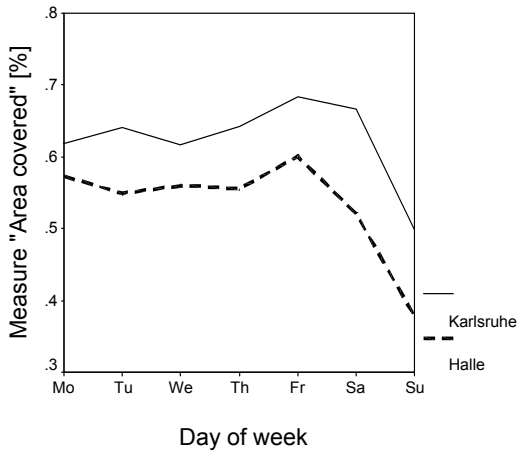
Volume against cells (Copenhagen control period)



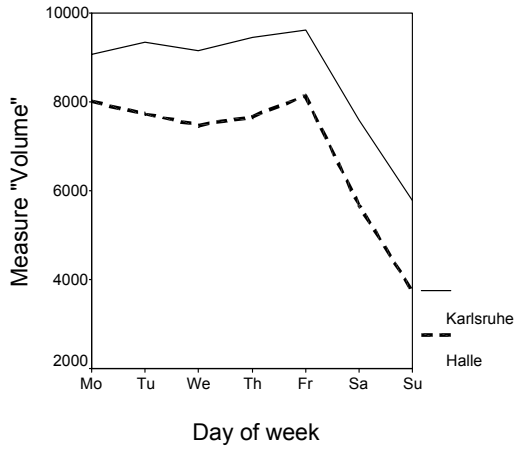
A differentiation by weekday underpins this strong linkage between travel volumes and both kernel density measures (Figure 56). There are only slight differences between the measures which get obvious for the weekend days. Whereas the measure based on the number of non-zero cells has its peak on Fridays and Saturdays, there is a considerable decrease in the value of the volume measure from Friday to Saturday and Sunday. This implies that the latter travel intensity indicator is somehow more frequency sensitive than the other indicator. Hence, the dispersion aspect of activity spaces (i.e. the distribution of activity locations in space) is out-weighted by the level of general mobility respectively the level of activity performance at the particular destination per time unit.

Figure 56 Kernel densities by weekday (Mobi*drive*)

Area covered*



Volume (Sum of kernel densities*1000)

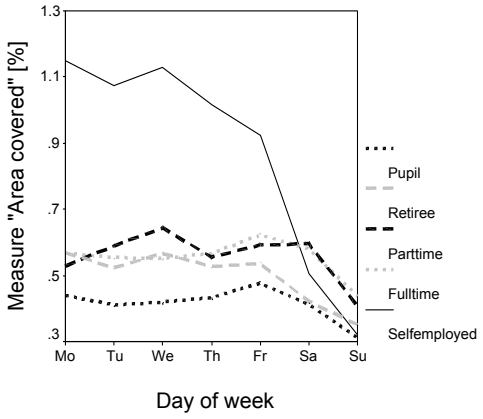


* Percentage of space covered by cells of positive kernel density

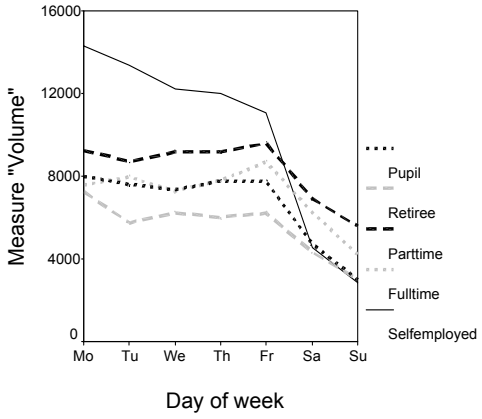
Turning to selected socio-economic factors influencing the density measures, again there are parallels to the general structures of daily mobility demand. Figure 57 makes clear that the occupation and lifecycle stati affect their magnitude. Working respondents have significantly higher values during the working days of the week compared to e.g. retirees or pupils. For the weekend days, the figures for the socio-economic groups converge.

Figure 57 Mean values of proposed measures by day of week and selected socio-economic groups (Mobi*drive*: Halle)

Area covered*



Volume



* Percentage of space covered by cells of positive kernel density

Shortest paths networks

Finally turning to the *shortest paths network* measure, the length of the geometry is in the centre of the analysis. The measure gives the sum of length of all used network links. Due to missing network data for most of the surveys, the measure could be generated only for Karlsruhe (Mobi*drive*) and Borlänge. It considers link lengths of regional road networks. Note that the Karlsruhe results cover all purposes and modes, whereas Borlänge yields results for car trips only.

The distribution of the Mobi*drive* sample is again Gamma-like distributed. As the length of the monitoring period scatters widely for the Borlänge respondents, the results were standardised by the number of monitored days in Figure 58. The distribution is similar.

Shortest path networks are again closely related to the volumes of travel. An initial analysis indicates that there are mainly two (interrelated) factors influencing the spanning tree's characteristic. First, the size of the tree is affected by the volume of travel and the spatial dispersion of the places visited. The measure therefore reflects the dispersion of the activity pattern – in line with the other measures (Figure 59). Second, the weighted geometry (link length multiplied by frequency of usage) is directly bound to the overall group-specific travel demand (Table 36). The differences of tree lengths between the socioeconomic groups confirm

the common findings on the determinants of travel demand. The variation coefficient (standard deviation / mean * 100) indicates that the relative variation is high for students, whereas the group-specific distribution of the measure is in particular low for fulltime workers with potentially more similar daily activity patterns compared to the others.

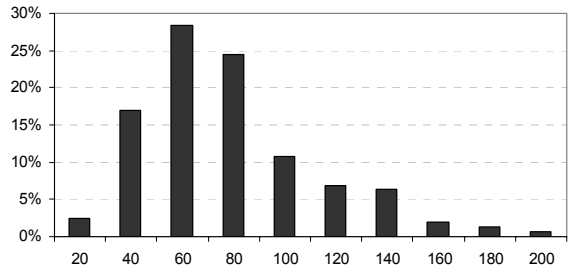
Table 35 Distribution of activity space sizes measured by shortest paths networks (km)

Survey			Length				Length weighted by frequency			
	N	Mean N days	Mean	Std.	Median	Skew-ness	Mean	Std.	Median	Skew-ness
Mobi*drive* Karlsruhe (all modes/purposes)	159	38	68	34	64	1.1	232	131	201	1.5
Borlänge (car trips)	66	205	1243	669	1157	0.8	4418	2904	3736	1.2

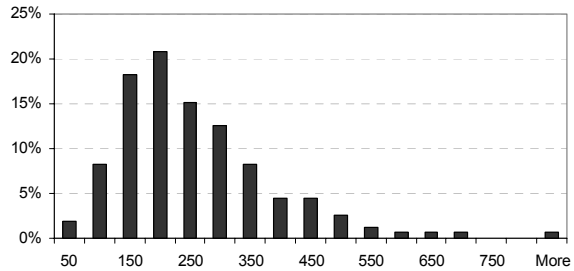
Figure 58 Distribution of activity space sizes measured by shortest paths networks: Length of used network [km]

Mobi*drive* Karlsruhe

Unweighted

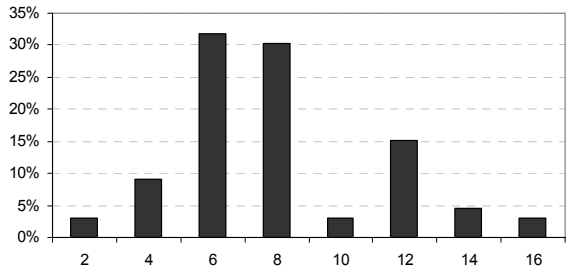


Weighted



Borlänge (divided by number of monitored days!)

Unweighted



Weighted

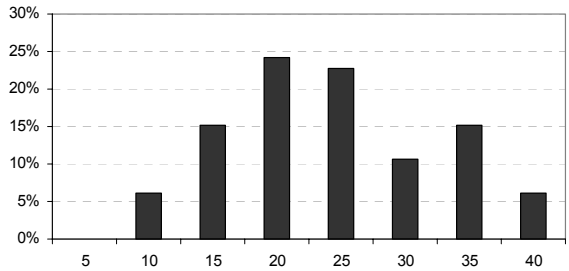
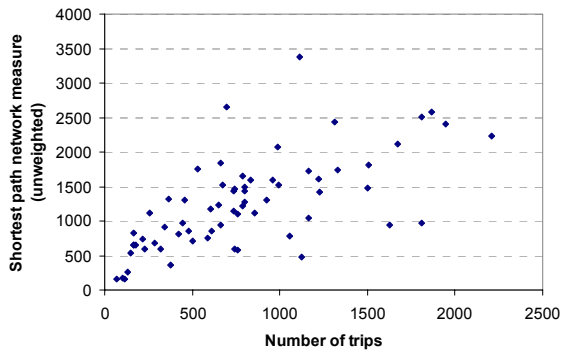


Figure 59 Activity space represented by shortest path networks: Measures versus number of trips and number of unique locations

Borlänge (unweighted)



Mobi*drive* (weighted)

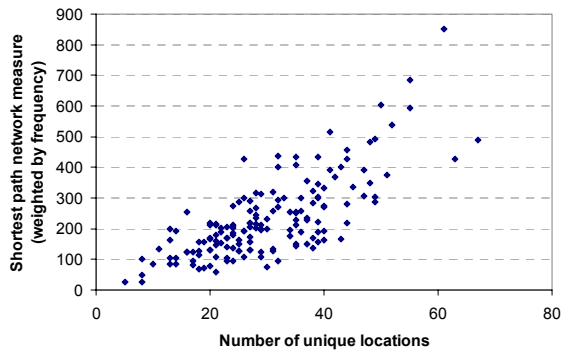


Table 36 Means of shortest paths networks by socio-economic groups (Mobi*drive*: Karlsruhe)

Occupation status	N	Mean unweighted** tree length [km] (Std.)	Mean ratio weighted / unweighted tree length	Std.	Var. Coeff. [%]
Student	7	79 (43)	2.32	0.88	38
Apprentice	6	72 (26)	3.31	1.01	30
Self-employed	8	110 (49)	3.61	1.11	31
Retiree	28	66 (32)	3.06	0.94	29
Pupil	27	68 (31)	2.77	0.75	27
Parttime	21	91 (36)	3.07	0.76	25
Fulltime	47	74 (36)	3.07	0.72	23
Housemaker	10	94 (45)	3.25	0.74	23
Unemployed	1	13 (-)	1.99	-	-

* Including home

8.4 Summary of the results concerning the continuous representation of activity spaces

The shown distributions of the proposed activity space measures indicate a great variety of sizes between travellers and between the different surveys. However, a great amount of the differences could be simply explained by the amount of travel observed during the survey and monitoring period. Each of the measures obviously correlates with the amount of travel, i.e. the number of trips made over the period of reporting. This is especially true for the volume measure (kernel densities) where there is an almost one-to-one correlation. At first sight, this finding seems to be unattractive. One could ask if an indicator for the size of individual activity spaces is useful which tells us that the structures of spatial mobility are tied purely to the amount of travel. At the same time, though, the outcome of the investigation strongly confirms our expectations. It indicates that the usage as well as the up-to-date knowledge or urban space is a function of the amount of contact a traveller has. This again has strong implications for the interpretation of the analysis results.

8.5 Activity space sizes and personal characteristics

Following the descriptive analysis of the measurements, which in itself is providing information never provided before, the thesis will finally link the measurement of the activity spaces to selected socio-economic variables describing the respondents. This final analysis covers the Mobi*drive*, Thurgau and Uppsala travel diary data as well as the Borlänge, Copenhagen and Atlanta GPS observations. As already mentioned above, the calculation of the continuous activity space measures was not performed for the latter data set. Besides, the Leisure study data was not considered here due its focus on one trip purpose only and the different level of resolution for the destination geocoding.

An analysis of covariance is performed to test selected personal attributes for their effects on activity space structure and size. These are the number of locations, the concentration of trips in few unique locations, the clustering of activities and the size of the local activity space indicated by the size of confidence ellipse, kernel densities and shortest paths networks (Table 37). Due to the limitation of socio-economic attributes for the drivers in the GPS observations, the analysis focuses on few covariates which are sex, age, occupation status, intensity of car usage and home location. Besides, the combined effect of car usage and agglomerational type(s) are added. For Mobi*drive* at least, further relationships were tested elsewhere (Schönfelder and Axhausen, 2002; Schönfelder and Axhausen, 2003b).

Table 38 shows in a reduced form whether the chosen attributes have an impact on the activity space indicator based on an analysis of variance (SAS General Linear Model (GLM) framework). A bold square for the respective classification variable or the combination of two means a significant main effect ($p<0.05$) on the dependent variable.

The GLM combines an analysis of variance type approach for the categorical variables with a regression type analysis of continuous variables. The significance levels reported above imply that one or more of the categories of a variable are significantly different from the survey samples.

Table 37 GLM by data source, activity space indicator and model: Variables

Variables	Description	Survey particularities
Locations	Mean number of locations/week	
Ratio	Locations per trips	
Concentration	Cumulative share of trips directed to 5 most important reported locations	
Clustering	Number of real cluster over entire reporting period	
Ellipse area	Size of 95% confidence ellipse of local trips analogous to description above (local trips)	Not for Atlanta
Kernel: Cells	Number of cells exceeding kernel density of zero	Not for Atlanta
Kernel: Volume	Sum of kernel densities	Not for Atlanta
Shortest path network unweighted	Length of shortest path network	Mobi*drive*/Karlsruhe and Borlänge only
Shortest path network weighted	Length of shortest path network weighted by frequency of usage	Mobi*drive*/Karlsruhe and Borlänge only
Covariates		
Sex		
Age	Age classes: < 30, >= 30 < 40, >= 40 < 50, >= 50 < 60, > 60	
Household size	Types: Single household, two persons, three and more persons	Copenhagen: no information available
Occupation status	Types: Fulltime working, part-time working retired, pupil, other	
Income	Types: Low (<25% percentile), medium 1 (25-50 percentile), medium 2 (50-75 percentile), high (>75 percentile) of respective survey sample	Uppsala: no information available; Copenhagen: no high income class

cont.

Car	Intensity of car usage Respondent is non-regular / regular car driver	Mobi*drive*, Thurgau, Uppsala: More than 50% of all trips made by car Borlänge: >10.000 km yearly kilometrage or more than 50% of trips stated to be made by car Copenhagen: >10.000 km or frequency of car usage to work per week >= 5 Atlanta: driver does not share car
Urban	Household location type 1: Agglomerational type urban/non-urban	Mobi*drive*, Copenhagen, Atlanta: all households;
Density	Household location type 2: Potential supply of facilities and shops in the vicinity of home	Mobi*drive*, Uppsala, Borlänge: all households, Thurgau: all households in the town of Frauenfeld, Borlänge: all households in inner-Borlänge, Copenhagen: all households in Greater Copenhagen; Atlanta: all households located less than 50 km away from Atlanta downtown
Combination of: Car * Urban Car * density Urban * density		

Table 38 Summary of the GLM results by data source, activity space indicator and model: Significance levels

Study	Mobi*drive* all trips of all respondents									Thurgau all trips of all respondents							Uppsala all trips of all respondents						
Variable	Locations	Ratio	Concentration	Clustering	Ellipse area	Kernel: Cells	Kernel: Volume	SPN not wei.	SPN weighted	Locations	Ratio	Concentration	Clustering	Ellipse area	Kernel: Cells	Kernel: Volume	Locations	Ratio	Concentration	Clustering	Ellipse area	Kernel: Cells	Kernel: Volume
Sex		■	■										■								■	■	■
Age	■	■		■		■			■	■	■	■		■			■		■			■	■
Household type		■		■						■					■								
Work status								■	■					■				■					■
Income		■	■			■	■		■						■								
Car usage	■	■	■		■	■		■	■	■	■	■		■	■	■		■	■		■	■	
Urban																							
Density												■	■	■	■	■							
Car * Urban																							
Car * Density											■	■	■	■									
Urban * Density																							
N	316	316	309	316	316	316	316	158	158	229	229	229	229	228	229	229	143	143	143	143	143	143	143
R^2	0.12	0.15	0.12	0.05	0.14	0.16	0.07	0.16	0.21	0.14	0.26	0.26	0.11	0.35	0.29	NS	0.12	0.17	0.08	0.10	0.12	0.24	0.16

cont.

Study	Borlänge car trips									Copenhagen car trips							Atlanta car trips			
Variable	Locations	Ratio	Concentration	Clustering	Ellipse area	Kernel: Cells	Kernel: Volume	SPN not wei.	SPN weighted	Locations	Ratio	Concentration	Clustering	Ellipse area	Kernel: Cells	Kernel: Volume	Locations	Ratio	Concentration	Clustering
Sex																			■	
Age		■																■		
Household type																	■			
Work status																	■		■	
Income		■								■								■	■	
Car usage	■																■			
Urban																				
Density														■						
Car * Urban																				
Car * Density																				
Urban * Density																				
N	44	44	44	44	44	44	44	44	44	197	197	197	197	197	197	197	404	404	404	404
R^2	Models as such not significant (NS)													0.06	NS		0.08	0.04	0.10	NS

■ Significance level <0.05, RSS is weighted by number of reported weeks; Type I sum of squares relevant for significance test

The models have only a poor fit in most cases - some of the models are not even statistically significant as a whole. This is somehow contradictory to the strong relationships of the measures with the amount of travel shown above. However, this shows that there is only an indirect link between the socio-economic attributes of travellers and the indicators of activity space size and structures. Besides, disaggregate models of trip generation based on small subsamples often suffer the same lack of explanatory power which is an indication of random variance and the difficult predictability of individual travel amounts.

Nevertheless, there are some explanatory trends detectable which is worth considering given the limited number of covariates and the small sample sizes for the regular car drivers data and the GPS observations. A consistent pattern is the effect of car usage for most of the given activity space characteristics. The impact of age and there lifecycle-group membership is another clear trend observable. Where urban density (i.e. potentially better conditions for a more efficient organisation of daily life and avoiding car usage) is a covariate like in the Thurgau survey, interactions with the activity space size becomes evident. Is car usage combined with density indication the effects are even amplified. Further significant effects could be analysed for sex (Uppsala) and income (Mobi*drive*).

It was expectable that lifecycle group membership shapes the size and structure of human activity spaces due to the different activity demand structures and commitments in the different stages of life. The most important results are however the effects of mobility tool ownership on the one hand, and location of the household on the other. Activity spaces are obviously influenced by the possibility to travel fast, comfortable and “timetable-less” – strongly positive as shown above. Car usage – based on car access and availability – is a definite determinant of destination choice. Finally, travellers tend to (or better: are forced to) increase their activity space if the home’s environment does not offer enough opportunities to satisfy activity demand of different purposes.

9 Summary of key results and methodological conclusions

Before turning to the policy implications of the analysis (Chapter 10), a compact summary of the key results is combined with some methodological conclusions:

9.1 Summary of key results

The studying of the rhythms of daily life has generated interesting new findings about the structures of daily travel and its determinants. This is in particular true for the analysis of revealed human activity spaces which have not been investigated in this detail before. The analysis followed the fundamental principles outlined in Chapter 4 and underpinned the demand for a further consideration of the issues in ABA.

(1) It could be shown that the usage of longitudinal travel data is a promising approach to reveal the structures of activity demand and spatial choice. The analysis made use of a wide range of variables which allowed to study the fundamental patterns of the temporal and spatial structures of travel. In addition to that, the most important motives based on the travellers' socio-economic attributes could be identified. The great exactness in the georeferencing of trip destinations was key to develop approaches to measure human activity spaces for the first time. Combining the travel diary data and the GPS observations was encouraging for future work. Results based on the extremely long GPS monitoring periods confirmed the trends revealed in the diary data. Although the data processing of the GPS observations is complex, challenging and need to be advanced in future work; the level of quality of the data was great enough to satisfy the analytical needs.

(2) The study made use of approaches of econometrics and geographical analysis. The richness of the data and the missing analysis experiences were major drives to test methodologies which are not common practice in travel analysis.

(3) The results are useful for research and planning. They are in particular a starting point for a methodological and practitioners' discussion about the current assumptions of individual destination choice.

The results of the models using socioeconomic covariates have only moderate explanatory power. However, models of disaggregated behaviour underlie great random variance which partly mirrors the imperfect predictability of human action.

Rhythms of activity demand and hazard modelling

The main results of the modelling of the periodicity in activity demand were in detail:

(1) The structures of activity demand differ significantly for the different trip purposes. The (relatively) fine categorisation of trip purposes was helpful to reveal underlying demand structures.

(2) Occupation status and car availability/usage are predominant determinants of the periodicity of daily life. This finding is in line with a range of other disaggregated models of human behaviour and indicates (a) the still strong dominance of the main activity of the different socio-economic groups (especially work) and (b) the restrictions respectively the degree of freedom which are imposed by the precommitment for a certain mobility tool (see also Axhausen, 2002).

(3) Household size and household structures are further strong travel behaviour controlling attributes. This is especially true for the temporal structures of leisure travel and shopping.

(4) Precommitments such as dog ownership or club membership shape the temporal structures of activity demand which shows that the survey design practice need to put a strong focus on the querying of these information. Long-term decisions such as community commitments tend to have strong implications for short-term choices in time and space.

(5) The different regional context of the surveys does not seem to have a significant impact on the temporal patterns of trip making and activity demand. Whereas travel volumes, durations and distances might differ, underlying temporal demand structures obviously are not necessarily affected by the traveller's home location.

(6) The modelling of the intervals of activity demand using techniques of survival analysis yielded a not entirely uniform picture. This concerns the comparison of the model approaches as well as the effects of the covariates chosen between the surveys. The chosen covariates obviously represent only part of the total determinants of the regularity in travel – which was expected.

The analysis has shown that most of the guiding research questions (hypotheses) relating to the periodicity of travel behaviour could be confirmed:

- There exist different patterns of regularity for different activity types.
- Non-obligatory activities, in particular leisure, show rhythmic structure, too (see e.g. stroll)
- The rhythmic structure of activity demand has a large amount of background variability and flexibility.
- The definition of a level of detail of analysis dictates the level of regularity in travel.

Applying hazard models to the analysis of the periodicity in travel behaviour successfully adds to the toolbox of the activity-based approach. Clearly, the question is raised if the conceptual model to represent the periodicity of activity demand in this thesis is appropriate. The proposed concept of an *increase in demand* could be tested as an explanatory pattern for some of the considered activity types – for example stroll. For other activity categories, the increase-in-demand-concept seems to be too inflexible as it interferes with the spontaneity and flexibility the human activity system and the scheduling of daily life inhabits. Modelling of the regularity in demand eventually requires a variable treatment of the different activity categories. However, important motives of the rhythmic structure of daily life could be identified (see above).

The application of the models has shown that there are challenges for future work. While the empirical inspection of the interval duration data for example by non-parametric models turned out as a straightforward analysis of the inherent temporal structure, the development of more sophisticated parametric models obviously requires

- a more purposeful selection of covariates by means of detailed tests instead of an intuitive selection approach
- a further discussion about reasonable distributional assumptions for the restrictive fully-parametric approaches
- the inclusion of censored times which were omitted so far and
- the integration of *heterogeneity effects* caused by the behavioural differences within the sample, the effects of repeated events and state dependency
- the consideration of more complex behavioural patterns (level of analysis detail, see above)
- the distinction of different kinds of events (*competing risks*)

- the consideration of covariates which describe preceding behaviour patterns such as the last interval length or the last duration of the same activity.

The latter aspect will stress the dynamic character of the model approach as it would stress the scheduling of activities over prolonged periods of time.

In addition to that, it still remains open if time-use and travel behaviour may be assumed to be homogenous across the whole sample. Using the Mobidrive data, more sophisticated hazard models were already developed and successfully applied (Bhat, Srinivasan and Axhausen, 2003; Bhat, Frusti, Zhao, Schönfelder, Axhausen, 2004). Compared to the basic AFT and Han and Hausman models implemented in this thesis, these models have a more flexible model structure which better capture aspects of unobserved heterogeneity and the dynamics of the temporal sequence of activities.

However, the presented conceptual model generally relates to parallel developments of ABA and the modelling practice in transport planning. The model approach interrelates with developments in the microsimulation of the activity scheduling of persons and households. The model results might act as an input for computational process modelling (CPM) tools which have a natural interest in information about the temporal allocation of recurrent behavioural patterns and its determinants.

The representation and measuring of human activity spaces

The enumeration, mapping and transformed representation of the observed trips and locations reflects an empirical confirmation of conceptual approaches of transport geography. Moreover, it provides a better insight into the structures of spatial choice. The guiding research hypotheses, i.e.

- the dominance of the daily destination choice structure by a few locations,
- the existence of a permanent discovery process of new locations and a constant innovation rate,
- a stable size of the activity space over longer periods and
- activity clustering behaviour

could be widely confirmed.

The major finding is clearly the ambiguity between strong habits and variety seeking in spatial behaviour. On the one hand, the concentration of trips into few predominant destinations

is large; on the other hand, the innovation or discovery rate of "new" places remains stable even after many months of monitoring. Furthermore, while the activity space size in total remains mainly the same due to the general limitations of given time budgets and speeds, new places are regularly searched beyond the boundaries of one's daily "home range".

The *continuous representation of activity spaces* measures turned out to be visually impressing, but limited in their expressiveness. The three shown measures are nevertheless models of human behaviour and simplifications of environmental perception and actual decision processes. Turning to these simplifying features of the proposed measures, there are some critical issues to discuss, such as

- the over-representation of actually used urban space – especially with the confidence ellipse measure ("Is the area covered by the geometries actually used or perceived by the travellers?")
- the restricted range in shape and the fact that the resultant figures of the activity spaces (confidence ellipses) are necessarily symmetrical
- the assumption of the continuousness of space usage and knowledge pretended by the geometric shapes of the measures ("Do we really perceive, know and use urban areas in a continuous way? Should we rather represent spatial behaviour by indicators of contact with single features of the environment, such as activity locations, landmarks, network sections or important junctions?")
- the missing indication about what 'happens' in and between the subcentres of daily life (mode choice, share of duration etc.) and about the interactions between the accessibility of locations and the behavioural outcome
- the strong impact of the frequency of travel on the measurement results, especially for the kernel densities and shortest path networks ("If there is such a high correlation between the size of the activity space and the individual amount of travel, what is the extra gained by an investigation of activity spaces and their determinants?")
- the sensitivity of threshold values and its implications for the magnitude of the results, e.g. the bin range, the cell size and the threshold for the consideration of densities for the kernel density measure.

Taking these points into account, the development of the measures is a substantial contribution to the analysis of long-term travel behaviour. As for other analysis tasks based on longitudinal data sets, there are only few indicators for the stability and variability of travel behaviour available. The techniques applied should not only be judged by their technical shortcomings or benefits, but also by what can be learned for the practice of human geography and transport. As Raine points out: "the calculation of ellipses as means of summarizing the point distributions did allow the analysis to reach beyond the purely descriptive level of terms such

as ‘random’ or ‘clustered’ and to say something more about their key spatial properties” (Rained, 1978, 331). Moreover, the activity space measures are certainly helpful for comparative purposes, i.e. the investigation of differences in spatial behaviour between respondents. Finally, the application of the measures will help to generate and test new hypotheses about point patterns and for summarising data

9.2 Further data implications

The small sample sizes do certainly affect the expressiveness of the results shown – however, at least the travel diary samples have great representativeness. The small number of respondents –especially for the Borlänge data which furthermore lacks important socioeconomic information of the drivers – has mainly implications for the stratification of the samples as group sizes become rather small to capture appropriate bandwidths.

As in every descriptive analysis of choice behaviour the question may be raised if the aggregation of individual responses is adequate. A wider differentiation by socio-economics could be an issue in further work on destination choice using the GPS data – in particular by using more explorative methods such as choice models.

As mentioned above, GPS data structure and processing issues considerations should be taken into account if interpreting the outcome. In addition to that, there is a bias to be expected due the initial character of the post-processing with the rough threshold approach to eliminate suspect trips/activities or the missing identification of the actual driver. As already mentioned a further main field of prospective work is the linkage of activity purposes to destinations and trips – imputed by suitable approaches such as the joining of land-use information. This would support the differentiation of unique locations by the actual motive of travel.

The comparability of data sets remains a big challenge for further analysis. This study tried to harmonise the data sets where necessary – mainly by a weighting of the observation lengths. This revealed similar structures of long-term decisions in space. However, the approach obviously needs to be supplemented by a more sophisticated weighting by socio-economic attributes of the travellers as the explanatory models did not entirely satisfy the researcher’s interest in detecting common underlying motives and determinants of behaviour.

9.3 Implications for travel behaviour analysis and further work

The results act as a reference basis for future research in travel behaviour analysis. The following issues are a – without doubt incomplete – listing of potential areas of methodological development and behavioural analysis.

Rethinking concepts of the spatial organisation of activities

The analysis made clear that existing theoretical concepts of the human activity space need to be partly rethought. There is some evidence that the often supposed bipolar structure of daily life travel which is believed to be constituted between home and work respectively home and school is vanishing. Whereas home is an undoubted peg or anchor of most activity spaces, the workplace seems often more isolated in terms of activity clustering as so far assumed. In addition to that, one could question if the other (minor) activities are spatially organised between work and home as authors have argued in the past (Holzapfel, 1980). Investigating the distribution of activities in urban areas, there is indication for a less organised locational choice apart from one's home area.

Predicting spatial choice

One other interesting issue in further research will be the potential for predicting spatial choice and activity spaces. Will we be able to make reliable assumptions about the socio-economic impact on the personal activity space? And is there a chance to "reconstruct" human activity spaces based on the observed equilibrium of the perceived choice set, individual innovation rates and one's aspiration for variety seeking in general? What we could show so far is that the amount of travel directly affects the number of unique locations. Even if the latter number not necessarily leads to a greater dispersion of visited places and therefore to a larger activity space, the same determinants which control the amount of mobility will have a big impact on the perception, knowledge and acquisition of urban space as well as on the personal innovation rate in spatial choice. Furthermore, if the structure of the activity space is a function of the places known and again, the observed extent and the consolidation of an individual innovation rate, activity spaces might be predicted to a certain extent.

Is there an "ideal" length of longitudinal surveys?

The analysis added to our knowledge about the level of the stability of individual travel behaviour and the deviations from a widely routinised daily mobility. From a survey design point of view the question arises if the results can be used to estimate a minimum duration of

longitudinal surveys – similar to those used here. In other words, what might be the ideal length of a consecutive days (weeks) panel survey which captures a maximum of intra-personal behavioural variability? This discussion was also led by Schlich (2004) who was using the 6-weeks Mobi*drive* data to identify homogenous groups of behaviour based longitudinal observation. The empirical results on destination choice over time – especially on the development of typical repertoires of regularly frequented locations – indicate that about two to four weeks of reporting seems to be an acceptable duration. Schlich proposes a similar length for travel diary surveys considering the temporal variations in travel. However, an ideal length of longitudinal surveys remains subject to the analyst's need for certainty about the individual level of routines: Does for example a capturing of 75% of intra-personal variability mean a good explanation of human behaviour over time or an insufficient?

Is there a balance between individual innovation in destination choice and the innovation of the dynamic travel environment?

Another field of potential investigation is the interaction between the shown aspirations for variety seeking in destination choice and the dynamics of the (travel) environment. Although stable in the short term, spatial properties of the built environment change due to – at best – innovation and development or a detoriation of space and land use. Without doubt, innovation in behaviour is affected by those trends in space – with for example altered "search spaces" for new locations to be discovered. A combination of data sources which cover long-term behavioural data and land-use information and their dynamics (e.g. GPS observations plus point-of-interest data) might reveal interesting findings about the balance, synchronization or time-delays between these two phenomena. In travel behaviour research, the investigation of long-term dynamics and the impact of external factors on behaviour is still rare. One of the few fields of exploration of such dynamics is car ownership using panel data such as for example in Landsman (1991). Landsman developed a dynamic model which associated deviations in household travel patterns from mean travel patterns with changes in car ownership over prolonged periods. A similar approach seems promising.

Interaction between destination choice patterns and the perception and existence of activity opportunities

A related direction of analytical interest is the relationship between supply and demand structures of spatial choice – i.e. the effect of individually perceived and/or actually existing accessibility of places. The enumeration of daily activity locations and the analysis of the distribution of such places (≈ *activity space*) revealed demand structures which may be seen as a joint consequence of

- individual choice preferences
- mobility tool ownership
- the spatial supply of activity opportunities.

In this thesis, the latter aspect and its impact on destination choice over time was not touched explicitly. Travel behaviour research has already started to investigate how the accessibility of places shapes the size and structure of activity spaces (see e.g. Miller, 1991; Kim and Kwan, 2003) – however, an examination of that relationship which takes a long-term perspective (i.e. using longitudinal data) is still missing (see also next section for the implications for planning).

Size and structure of individual choice sets

Finally, the results on locational choice have the potential to influence current practice in transport modelling. The investigation will deepen the discussion on the size and structure of the individual choice set in destination choice. As discussed above, modelling widely assumes that all spatial alternatives are known to the traveller which allows create an arbitrarily composed choice set for estimation. This assumption goes back more than 100 years to Lill's (1889) paper on the *Grundgesetze des Personenverkehrs* (basic laws of personal travel). The analysis of longitudinal data sets has shown that this practice eventually leads to biased parameter estimates, as the alternatives of which the traveller is aware are limited, clustered and unevenly known. Observed spatial behaviour is a tradeoff, which cannot be replicated by a random sample of alternatives. The results imply that choice sets are likely more condensed than so far assumed. The concentration of a large share of trips in few locations underpins the notion of spatially stable behaviour over time (see also Buliung and Roorda, 2005). The application of the activity space measures has for example shown that we can define a (fix) area for each individual which contains 90 to 95% of all potential places of interest. This finding is an indicator of the structure of choice sets and might help to better define the probability of locations of being a potential alternative. However, the analysis has also shown that the challenge of defining appropriate choice sets lies in travellers' desires and needs for variety seeking in spatial choice.

10 Implications for policy and planning

Finally, some remarks will be made concerning the potential policy and planning implications of this work. They touch the question of how to influence travellers' mobility patterns given the strong behavioural routinisation shown and the potential of the activity space measurement for the design and evaluation of the built environment.

10.1 Habitual behaviour and travel choices

The analysis has shown that travel is a function of needs and commitments which have a more or less regular character. In addition to that, travel behaviour has also strong roots in the habitulisation of temporal and spatial choices which is a legitimate way of evading decision situations which cause additional (new) search efforts. This could be shown for the timing of activities as well as for the destination choice structures. From the perspective of the individual, habits appear efficient, however controllable and target oriented which is an attractive feature compared to permanent new decision making.

The differences between a behavioural routine and a deliberate action or choice are manifold (see e.g. Fishbein and Ajzen, 1975): Whereas a deliberate action needs a certain motivation for decision – for example a "risky" outcome –, a routinised choice is made because the decision is obviously irrelevant. Besides, deliberate actions are taken since usually there is enough time to decide and the decision maker has sufficient cognitive capacity to evaluate the pros and cons of her/his choice.

Habitulisation of choices is often also a sign for the missing or poor awareness of better alternatives and the real costs connected with those chosen instead. This leads to unfavoured situations such as congestion which not only have negative effects for the individual but for other travellers as well. Hence, habits and routines of travellers are often contradictory to behavioural changes which are favoured by transport policy and which would be necessary for a more efficient transport system.

As a consequence, a better knowledge and understanding of habitual behaviour and the determinants of routines in trip making and activity demand are crucial for public planning and

regulation. This is because travel behaviour analysis, environmental psychology and related research fields need to analyse

- the characteristics and structures of habitual behaviour,
- the fundamental principles of decision making processes which lead to habitual travel choices and
- the best strategies to influence unfavourable behaviour and break routines (Gärling and Axhausen, 2003).

From a planning point of view, the interdependency of routinised behaviour and attitude is still one of the keys for a manipulation of the travellers. Interestingly, habitual behaviour is often independent of and conflicting with own attitudes and convictions. This makes it even more difficult to mediate policy measures successfully. As recent attitude surveys show, there is a persistent positive attitude for example towards the protection of natural resources as well as a prioritisation of public transport or local traffic calming schemes (e.g. ARE and BfS, 2001). Thus the question arises why positive attitude towards environmental protection have no consequences for the respective travel behaviour, for example by the lesser usage of motorised private vehicles which contribute considerably to local emission problems climate change.

This discussion has found its way into the studies of environmental psychology which identified mechanisms of the Normative Decision Making (NDM) theory (Schwartz, 1977) as one of the obstacles for behavioural change. In brief, NDM is a concept which tries to describe decision making as a multi-stage process which consists of the steps

- (signal / stimulus / problem emerges)
- problem realisation (attention stage)
- build up motivation for action
- assessing potential consequences of behaviour
- if assessment of last step is positive, behaviour is invoked

Psychologists discuss two possibilities of how routines negatively affect this logical order of steps (Klöckner, Matthies and Hunecke, 2003): First, habits block the decision process as certain signals automatically provoke (routinised) actions. In other words, there exists a direct link between stimulus and response which bypasses the attention stage as well as the motivation for and the evaluation of an action. Second, habits might affect the assessment or evaluation stage and in particular the assessment of so called non-moral consequences such as po-

tential time losses or expenditure. Individuals obviously rate saved time due to inhibited efforts to search additional information more positive than a new choice with yet uncertain consequences or costs.

Hence, planning may influence bad routines only if a few preconditions are met:

- the initialising of a more conscious process of decision making which consists of the steps "stop old behaviour", "store the good intention", "a multiple testing of the new solution" and "the repeated choice of the new solution"
- the formulation of an individual intention for change is supported
- the alteration of the decision context, i.e. the impeachment of old (bad) attitude and individual targets, the modification of rewards and penalisation of available options.

The investigation of the Copenhagen pricing experiment has shown that cordon pricing as a measure which significantly alters the decision context by the introduction of a penalisation system has a strong impact on routinised spatial choice decisions. This is especially true for the distribution of trips and destinations by zonal order. However, the level of analytical resolution applied yielded also partly ambivalent results which partly have their roots in behavioural obstacles for change. Principally, activity demand and especially destination choice is not uncoupled from commitments and constraints of daily life which reduces the degree of freedom for alternative choices.

In principle, successful strategies need to differentiate between choice situations where deliberate action is feasible and those where habitual choices are predominant and eventually avoidable. Existing studies with a focus on mode choice show that measures which take this point into account are more successful than those which neglect these preconditions (Bamberg, 2000; Fuji and Gärling, 1999).

10.2 A more sustainable, fairer and healthier transportation system?

The enumeration of daily activity locations and the analysis of the distribution of such places have revealed both, the supply structure of activity opportunities in space and the destination choice behaviour of travellers given their perceived supply. This invites transport planning and research to once more evaluate present and imaginable future urban structures from the perspective of sustainable transport policy. This includes for example measures to increase the amount of the opportunities to satisfy the activity demand (i.e. potential destinations) in the

household's neighbourhood. This might successfully reduce individual (hidden) travel costs, further congestion and emissions. There is strong evidence that local accessibility oriented land-use planning matters (Banister, 2000; Simma, 2000). It should be not neglected, though, that the there are complexity and non-linearities within the interaction between locational supply and the actual choice of destinations.

Furthermore, the activity space issue has to be put on the agenda when discussing the relationship between poverty, the deprivation of urban areas and transport. Kenyon, Lyons and Rafferty (2002) argue that important determinants of the activity space such as poor or unavailable transport (e.g. car ownership) as well as reduced accessibility to facilities, goods and services are dimensions and factors of social exclusion. The size and structure of the activity space therefore may act as a – highly political – indicator of social justice and the efficiency of an infrastructure supply policy matching societal needs. The analysis of the samples revealed systematic differences between different categories of certain variables, but did not reveal clear classes of travellers with unusually small activity spaces. This study and the samples were not designed to address this issue in the first place, but a dedicated attempt to construct a sample with respondents, which can be considered to be at risk, might lead to different conclusions.

Finally, the activity space approach might get more attention in the wider context of physical activity analysis. Since the relationship of (the lack of) physical activity and health was identified to be one of the key challenges in the developed world (WHO, 2004), suitable indicators of activity and movement will be needed to identify necessary strategies to support physical exercise. Transport and urban planning are key actors to provide a *walkable* and *cyclable* environment. The discussion has already encouraged researchers to apply activity space measures to the investigation of related health issues such as functional assessment, level of disability or health care accessibility (Kopec, 1995; Sherman, Spencer, Preisser, Gessler and Arcury, 2005). Not necessarily a transport analysis concern by nature, the discipline will certainly be invited to provide its expertise in data collection and management as well as in the analysis of the relationship between the built environment, infrastructures, the supply of transport services and human movement patterns.

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A 1 Activity purpose categorisations

Mobi*drive*, Thurgau, Uppsala

1 Serve passenger
2 Private business
3 Work related
4 School/education
5 Work
6 Daily shopping/Grocery
7 Long-term shopping
8 Leisure
9 Other
10 Home

City:mobil categorisation (see Götz, Jahn and Schultz, (1997)) – adopted

1 Work
2 Work related
3 School/Education
4 Further education/courses
5 Serve passenger
6 Daily shopping/Grocery
7 Long-term shopping
8 Window shopping
9 Private business
10 Meet family
11 Meet friends
12 Club, church etc.
13 Doctor, dentist, hair cut
14 Car service/cleaning
15 Active sports
16 Excursion into nature
17 Stroll
18 Excursion over weekend
19 Garden/cottage
20 Sightseeing
21 Going out (bar, restaurant, cinema etc.)
22 Home
23 Other
24 Graveyard
25 Voluntary work
26 Family related (parents' meeting)

A 2 Programme scripts

The calculations of results on the periodicity and the activity spaces were implemented in several software packages, but mainly in SAS, LIMDEP and ESRI ARCINFO. The syntax of the most important programmes will be documented in full detail on the attached CD-ROM. The following table gives a listing of script names and the reference to the respective chapter.

Table A1 Overview of most important programmes (scripts) developed

Analysis	Programme (script name)	Chapter
Rhythmic patterns		
Weibull AFT model	SAS: weibull.sas	6.6
Han and Hausman semiparametric model	LIMDEP: hanandhausman.lim	6.6
Enumeration exercise		
Volumes	SAS: volumes.sas	7.3
Stability/variability	SAS: basics.sas SAS: ratio.sas SAS: 10most.sas	7.3
Variety seeking	SAS: newlocas.sas	7.3
Binding effects	SAS: binding.sas	7.3
Innovation	SAS: innovation.sas	7.3
Development of activity space size	SAS: homedist.sas	7.3
Dispersion	SAS: dispersion.sas	7.3
Clustering	SAS: clusters.sas	7.3
Effects of pricing	SAS: order.sas SAS: zones1-3.sas	7.3
Ellipses	*See below*	*8.3*
Kernel densities	*See below*	*8.3*
Shortest paths networks	*SAS: relations.sas*	*8.3*

Appendices A3 and A4 give the source codes (SAS and ARCMacroLanguage (AML)) for the two most important activity space approaches confidence ellipse and kernel densities.

A 3 Confidence ellipse programme script°

```
/* Default variables: (locations:) xloc, yloc, (references such as weighted
means:) refx, refy */

/* Prepare base data: */

data dummy;
     set last.t_sum;
     if studycod = 1 then delete;
     if t_pur = 10 then delete; /* Only out of home */
     if local = 0 then delete;
*    if t_pur ne 8 then delete;
     x = gcwgs84x; y = gcwgs84y;
     person = 1000000 * citycode + 100000 + studycod + 10 * hh_nr + p_nr ;
     if x = . or x = 0 or y = . or y = 0 then delete;
run;

/* Calculate coordinates of weigthed arithmetic mean - if needed

data comp1;
     set dummy;
     squarex = x * x ;
     squarey = y * y ;
     x_mul_y = x * y;
run;


proc summary data = comp1;
     class person;
     var x y squarex squarey ;
     output
     out = comp2
     sum = x_sum y_sum sqx_sum sqy_sum
     ;
run;


data comp2;
     set comp2;
     if person = . then delete;
     sumfreq = _freq_ ;
     refx = x_sum / sumfreq; refy = y_sum / sumfreq;
     ID = person;
     keep ID sumfreq person refx refy;
run;

*/

/* Comp2: Household location  */

proc summary data = dummy;
     class person;
     var homex homey;
     output
     out=comp2
```

° Partly adopted and modified from Botte, 2003

```
     max=homex homey
     ;
run;


data comp2;
     set comp2;
     if person = . then delete;
     refx = homex; refy = homey; id = person; sumfreq = _freq_;
     keep person refx refy id sumfreq;
run;



/* Merge reference (mean) points - base coordinates*/

data dummy2;
     merge dummy comp2;
     by person;
     xloc=x; yloc=y;
     ID=person;
     keep ID xloc yloc refx refy;
run;


/* Calculate auxiliary values for covariance matrix, reference point here:
          WEIGHTED MEAN, other reference point (such as home) is possible
*/

data covhelp;
     set dummy2;
     SXX_HELP = (XLOC-REFX)**2;
     SYY_HELP = (YLOC-REFY)**2;
     SXY_HELP = (XLOC-REFX)*(YLOC-REFY);
run;

/* Sum auxiliary values 1 */

data sxxhelp;
     set covhelp (keep = REFX REFY SXX_HELP ID);
     by ID;
     if first.ID then SUM_SXX = 0;
     SUM_SXX + SXX_HELP;
     if last.ID;
     drop SXX_HELP;
run;

/* Sum auxiliary values 2 */

data syyhelp;
     set covhelp (keep= REFX REFY SYY_HELP ID);
     by ID;
     if first.ID then SUM_SYY = 0;
     SUM_SYY + SYY_HELP;
     if last.ID;
     drop SYY_HELP;
run;

/* Sum auxiliary values 3 */

data sxyhelp;
```

```
     set covhelp (keep= REFX REFY SXY_HELP ID);
     by ID;
     if first.ID then SUM_SXY = 0;
     SUM_SXY + SXY_HELP;
     if last.ID;
     drop SXY_HELP;
run;

/* Merge intermediate data sets*/

data covhelp1;
     merge comp2 sxxhelp syyhelp sxyhelp;
     by ID;
run;


/* Calculate variances and covariances (Jennrich and Turner)
Calculate ellipse area and angle between main axis and x-axis of local co-
ordinate system */

data covariance;
     set covhelp1;
     by ID;
     PI=constant('pi');
     if (SUMFREQ-1) > 0 then do;
     SXX = ((1/(SUMFREQ-1)))*SUM_SXX;
     SYY = ((1/(SUMFREQ-1)))*SUM_SYY;
     SXY = ((1/(SUMFREQ-1)))*SUM_SXY;
     DET_S = ((SXX*SYY) - (SXY*SXY));
     if DET_S < 0 then do;
          DET_S=DET_S*(-1);
          MERKER=1;
     end;
     AREA95 = round((cinv(.95,2) * PI *sqrt(DET_S))/1000000);
     PHI=(1/2*atan(cinv(.95,2)*(2*SXY)/(SXX-SYY)))*180/PI;
     end;
run;

/* Calculate eigenvalues and eigenvectors of ellipses  */

data eigenvalues;
     set covariance;
     by ID;
     /*if SXX<SYY then do;
          SYYalt=SYY;
          SYY=SXX;
          SXX=SYYalt;
     end;*/
     HELP1=SXX-SYY;
     HELP2=SXX+SYY;
     HELP3=sqrt((HELP1/2)**2+SXY**2);
     EVAL1=(HELP2/2)+HELP3;
     EVAL2=(HELP2/2)-HELP3;
     LAMBDA1=sqrt(EVAL1);
     LAMBDA2=sqrt(EVAL2);
     R1=sqrt(AREA95/PI*LAMBDA1/LAMBDA2);
     R2=sqrt(AREA95/PI*LAMBDA2/LAMBDA1);
     EV11=SYY-EVAL1-SXY;
     EV12=SXX-EVAL1-SXY;
     EV21=SYY-EVAL2-SXY;
     EV22=SXX-EVAL2-SXY;
```

```
     EVEC11=(EV11/sqrt(EV11**2+EV12**2));
     EVEC12=(EV12/sqrt(EV11**2+EV12**2));
     EVEC21=(EV21/sqrt(EV21**2+EV22**2));
     EVEC22=(EV22/sqrt(EV21**2+EV22**2));
run;

/* Calculate extreme values of ellipses (via parameter equations): base
weigthed mean or other reference point */

data extrema;
     set eigenvalues;
     by ID;
     E1=(2*pi*1/4);
     E2=(2*pi*1/2);
     E3=(2*pi*3/4);
     E4=(2*pi);
     S1=round(sin(E1),.001);
     S2=round(sin(E2),.001);
     S3=round(sin(E3),.001);
     S4=round(sin(E4),.001);
     C1=round(cos(E1),.001);
     C2=round(cos(E2),.001);
     C3=round(cos(E3),.001);
     C4=round(cos(E4),.001);
     X1HELP=sqrt(cinv(.95,2))*LAMBDA1*C1;
     Y1HELP=sqrt(cinv(.95,2))*LAMBDA2*S1;
     X2HELP=sqrt(cinv(.95,2))*LAMBDA1*C2;
     Y2HELP=sqrt(cinv(.95,2))*LAMBDA2*S2;
     X3HELP=sqrt(cinv(.95,2))*LAMBDA1*C3;
     Y3HELP=sqrt(cinv(.95,2))*LAMBDA2*S3;
     X4HELP=sqrt(cinv(.95,2))*LAMBDA1*C4;
     Y4HELP=sqrt(cinv(.95,2))*LAMBDA2*S4;
     X1=EVEC11*X1HELP+EVEC21*Y1HELP+REFX;/*REFX: siehe oben -> 0=HOME
XMEANWTLOC=MEAN*/
     Y1=EVEC12*X1HELP+EVEC22*Y1HELP+REFY;/*REFY: siehe oben -> 0=HOME
YMEANWTLOC=MEAN*/
     X2=EVEC11*X2HELP+EVEC21*Y2HELP+REFX;/*REFX: siehe oben -> 0=HOME
XMEANWTLOC=MEAN*/
     Y2=EVEC12*X2HELP+EVEC22*Y2HELP+REFY;/*REFY: siehe oben -> 0=HOME
YMEANWTLOC=MEAN*/
     X3=EVEC11*X3HELP+EVEC21*Y3HELP+REFX;/*REFX: siehe oben -> 0=HOME
XMEANWTLOC=MEAN*/
     Y3=EVEC12*X3HELP+EVEC22*Y3HELP+REFY;/*REFY: siehe oben -> 0=HOME
YMEANWTLOC=MEAN*/
     X4=EVEC11*X4HELP+EVEC21*Y4HELP+REFX;/*REFX: siehe oben -> 0=HOME
XMEANWTLOC=MEAN*/
     Y4=EVEC12*X4HELP+EVEC22*Y4HELP+REFY;/*REFY: siehe oben -> 0=HOME
YMEANWTLOC=MEAN*/
run;
/* Caluculate radius and length of main and other axis of ellipse */

data paraxes;
     set extrema;
     by ID;
     H=sqrt((X2-X4)**2+(Y2-Y4)**2);
     N=sqrt((X1-X3)**2+(Y1-Y3)**2);
     Rad1=H/2;
     Rad2=N/2;
     AREACHECK=PI*Rad1*Rad2;
run;
```

A 4 ARCINFO Macro Language (AML) script: Kernel densities

```
/* Displays and calculates activity spaces by using kernel estimation & AR-
CINFO GRID */

/* Create coverages for each traveller/vehicle

     &do count = 1 &to xxx &by 1
     ae
     ec points
     ef point
     &sv c = %count%
     sel vehicle = %c%
     &if [show number select] > 1 &then
       &do
          put vehicle_%c%
          quit
          tables
          additem vehicle_%c%.pat spot 6 6 i
          sel vehicle_%c%.pat
          calc spot = clusfreq * 100
          additem vehicle_%c%.pat mobility 4 4 b
          sel vehicle_%c%.pat
          calc mobility = 1
     &end
     quit
 &end
 &return


/* Actual kernel density estimation

&do count2 = 1 &to xxx &by 1
     &sv pcover = [exists vehicle_%count2% -cover]
     &if %pcover% &then
     &do
       grid
       setwindow atlwindow
       helpgrid = pointdensity(vehicle_%count2%, spot, 5000, kernel, 1000,
       1000)
     /* to create value attribute table
       vat_%count2% = int(helpgrid + .5)
       kill helpgrid
       quit
       tables
       additem vat_%count2%.vat counvalu 12 12 i
       sel vat_%count2%.vat
       calc counvalu = count * value
       end
       statistics vat_%count2%.vat result_%count2%
       sum counvalu
       max count
       sum count
       end
     &end /*if
&end
```

```
&return


/* Export statistics results to ASCII

&do count2 = 1 &to xxx &by 1
          &sv pinfo = [exists result_%count2% -info]

/* True or false, if true
          &if %pinfo% &then
          &do
               tables
               sel result_%count2%

/* Adds values to list/ASCI file
               unload value-total.txt sum-counvalu max-count sum-count
               &end
          &end
&end
&return

/* Deletes unneccessary grids

&do count1 = 1 &to xxx &by 1
          &sv pgrid = [exists vat_%count1% -grid]
          &if %pgrid% &then
          kill vat_%count1%
     &end
&return


/* Deletes unneccessary covers

&do count1 = 1 &to xxx &by 1
     &sv pcover = [exists vehicle_%count1% -cover]
          &if %pcover% &then
          kill vehicle_%count1%
     &end
&return


/* Deletes unneccessary result tables

tables
&do count1 = 1 &to xxx &by 1
          &sv pres = [exists result_%count1% -info]
          &sv pvat = [exists vat_%count1%.vat -info]
          &sv pbnd = [exists vat_%count1%.bnd -info]
          &sv psta = [exists vat_%count1%.sta -info]
          &if %pres% &then
          kill result_%count1%
          &if %pvat% &then
          kill vat_%count1%.vat
          &if %pbnd% &then
          kill vat_%count1%.bnd
          &if %psta% &then
          kill vat_%count1%.sta
     &end
quit

&return
```

A 5 Variables (results)

A file with the most important findings of the enumeration exercise and the activity space measuring is also stored on the attached CD-ROM[35]. It contains the following variables which are related to the respoendents respectively vehicles (where available):

[35] The results for the hazard models are documented in the text and/or in the following appendix.

Table A2 (Result) Variable names and descriptions

Variable name	Label
Area95	Confidence ellipse area: all purposes, all modes
Area95car	Confidence ellipse area: all purposes, car trips of regular car drivers
Area95Leisure	Confidence ellipse area: leisure, all modes
Area95LeisureCar	Confidence ellipse area: all purposes, car trips of regular car drivers
Cumshare5most	Share of trips of five most important unique locations (without home)
Cumshare5mostCar	Share of trips of five most important unique locations (without home), car trips of regular car drivers
HhiModePur	HHI index mode choice by purpose
KernelCells	Number of cells exceeding kernel density of zero
Kernelvolume	Sum of kernel densities (volume)
LeisureNDays	Number or reported or monitored (mobile) days – leisure trips only
LeisureNLocations	Number of unique locations (entire observation period) – leisure trips only
LeisureNTrips	Number of unique locations (entire observation period) – leisure trips only
NCluster	Number or reported or monitored (mobile) days
NClusterCar	Number or reported or monitored (mobile) days, car trips of regular car drivers
NDays	Number or reported or monitored (mobile) days
NDayscar	Number or reported or monitored (mobile) days, car trips of regular car drivers
NLocations	Number of unique locations (entire observation period)
NLocationsCar	Number of unique locations (entire observation period), car trips of regular car drivers
NTrips	Number of unique locations (entire observation period)
NTripsCar	Number of unique locations (entire observation period), car trips of regular car drivers
Ratio	Ratio unique locations to trips
RatioCar	Ratio unique locations to trips, car trips of regular car drivers
RegularDriver	Indicates if respondent is regular car driver (according to definition above)
SpnRatio	Ratio of weighted length of shortest path network to unweighted geometry

cont.

SpnUnweighted	Length of shortest path network (total length of network)
SpnWeighted	Length of shortest path network (total length of network weighted by frequency)

The results will be also archived in ETHTDA (Eidgenössische Technische Hochschule Travel Data Archive (ETHTDA) – either as additional data for the already archived or soon added travel data sets Mobi*drive*, Thurgau and Borlänge.

ETHTDA is a virtual platform for travel data and has been developed at the IVT since May 2002. ETHTDA allows users to view and investigate travel data and relating meta information via the internet. ETHTDA is one of the first archives of travel data which matches the technical requirements and standards of the Data Documentation Initiative (DDI).

Interested persons and institutions can download the data after requesting an ID and a password from the ETHTDA administration.

General access (without download permission):

http://www.ivt.baug.ethz.ch/vrp/ethtda.html bzw. http://129.132.96.89/index.jsp
login: guest
password: ethtda

Login and password may be ordered given a legitimate interest from Mr. Chalasani:

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For an **access to the original data sets** not stored at ETHTDA please contact the following institutions:

Uppsala:	Data are property of Prof. Susan Hanson; please contact Prof. Axhausen/IVT for details (axhausen@ivt.baug.ethz.ch)
Copenhagen:	Data are property of CTT, Danish Technical University; please contact Prof. Nielsen for details (oan@ctt.dtu.dk)
Atlanta:	Data are property of GeorgiaTech, Atlanta; please contact Prof. Guensler for details (randy.guensler@ce.gatech.edu)

A 6 Hazard model results for the different activity categories

Han and Hausman model estimation results

Variables:

SEX	Sex
AGE	Age
AGE2	Age squared
MARRIED / PARTNER	Is married / lives in fixed partnership
PARENT	Is parent
CLUB	Club member
FULLTIME	Fulltime working
DOGGY	Is dog owner
N_O_HHM	Number of household members
INCOME3	High income
N_O_PV / N_O_V	Number of personal vehicles
CAR_AVAI	Is main car user
CITYCODE / AGGLO	Karlsruhe / Frauenfeld

Mobidrive

Daily shopping

```
+---------------------------------------------+
| Ordered Probability Model                   |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 11, 2005 at 10:01:58AM.|
| Dependent variable             INTERVAL     |
| Weighting variable                 None     |
| Number of observations             3019     |
| Iterations completed                 31     |
| Log likelihood function       -5351.519     |
| Restricted log likelihood     -5409.232     |
| Chi squared                    115.4262     |
| Degrees of freedom                   12     |
| Prob[ChiSqd > value] =         .0000000     |
| Underlying probabilities based on Logistic  |
|    Cell frequencies for outcomes            |
|  Y Count Freq  Y Count Freq  Y Count Freq    |
|  0  1229 .407  1   651 .215  2   423 .140   |
|  3   240 .079  4   111 .036  5   103 .034   |
|  6    93 .030  7    42 .013  8    23 .007   |
|  9    26 .008 10    21 .006 11    20 .006   |
|   (cells 12-16 omitted)                     |
+---------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
	Index function for probability				
SEX	-.1696226551E-01	.81160236E-01	-.209	.8345	.41470686
AGE	-.6395351778E-03	.61090533E-02	-.105	.9166	45.633654
AGE2	.1871367245E-04	.78650007E-04	.238	.8119	2367.6999
MARRIED	-.1817390715	.85771146E-01	-2.119	.0341	.62139781
PARENT	-.5426819931	.94713434E-01	-5.730	.0000	.39483273
CLUB	.1884592387	.88178201E-01	2.137	.0326	.19642266
FULLTIME	.7109143291	.90022311E-01	7.897	.0000	.29943690
DOGGY	-.2600830026	.10180603	-2.555	.0106	.14541239
N_O_HHM	.1776272029	.36891937E-01	4.815	.0000	2.6435906
INCOME3	-.2669736857	.89907933E-01	-2.969	.0030	.26697582
N_O_PV	.8114867583E-01	.66856054E-01	1.214	.2248	1.1026830
CAR_AVAI	.2547396952E-01	.80727601E-01	.316	.7523	.43159987
CITYCODE	-.2008386951E-01	.71181933E-01	-.282	.7778	.51705863

Longterm shopping

```
+---------------------------------------------+
| Ordered Probability Model                   |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 11, 2005 at 10:13:50AM.|
| Dependent variable             INTERVAL     |
| Weighting variable                 None     |
| Number of observations             1031     |
| Iterations completed                 31     |
| Log likelihood function       -2469.143     |
| Restricted log likelihood     -2480.580     |
| Chi squared                    22.87527     |
| Degrees of freedom                   12     |
| Prob[ChiSqd > value] =         .2880370E-01 |
| Underlying probabilities based on Logistic  |
|    Cell frequencies for outcomes            |
|  Y Count Freq  Y Count Freq  Y Count Freq    |
|  0   232 .225  1   173 .167  2   109 .105   |
|  3    85 .082  4    71 .068  5    64 .062   |
|  6    86 .083  7    34 .032  8    36 .034   |
|  9    28 .027 10    21 .020 11    25 .024   |
|   (cells 12-16 omitted)                     |
+---------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
	Index function for probability				
SEX	.1738258386	.12601040	1.379	.1678	.41319108
AGE	.1570833386E-01	.12010624E-01	1.308	.1909	43.408341
AGE2	-.1287556869E-03	.16438207E-03	-.783	.4335	2179.4374
MARRIED	-.8738290302E-01	.14905452	-.586	.5577	.59262852
PARENT	-.3525122403	.15509884	-2.273	.0230	.35111542
CLUB	-.1834587036E-01	.13083002	-.140	.8885	.26091174
FULLTIME	.4111156599	.14973530	2.746	.0060	.30261882
DOGGY	.1324642493	.18325188	.723	.4698	.10669253
N_O_HHM	.1571940168	.57974298E-01	2.711	.0067	2.7633366
INCOME3	-.1675236668	.14975060	-1.119	.2633	.27449079
N_O_PV	.3611761810	.10855890	3.327	.0009	1.0931135
CAR_AVAI	-.5057803802E-02	.13240312	-.038	.9695	.41416101
CITYCODE	.2891256601E-01	.11475225	.252	.8011	.50921435

Private business

```
+---------------------------------------------+
| Ordered Probability Model                   |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 11, 2005 at 10:15:02AM.|
| Dependent variable             INTERVAL     |
| Weighting variable                 None     |
| Number of observations             2346     |
| Iterations completed                 32     |
| Log likelihood function       -4640.717     |
| Restricted log likelihood     -4696.993     |
| Chi squared                    112.5518     |
| Degrees of freedom                   12     |
| Prob[ChiSqd > value] =         .0000000     |
| Underlying probabilities based on Logistic  |
|    Cell frequencies for outcomes            |
|  Y Count Freq  Y Count Freq  Y Count Freq    |
|  0   898 .382  1   401 .170  2   279 .118   |
|  3   190 .080  4   128 .054  5   115 .049   |
|  6   103 .043  7    48 .020  8    44 .018   |
|  9    34 .014 10    23 .009 11    15 .006   |
|   (cells 12-16 omitted)                     |
+---------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
	Index function for probability				
SEX	-.4581336255E-02	.86540642E-01	-.053	.9578	.49445865
AGE	.1151464562E-01	.69813908E-02	1.649	.0991	45.514493
AGE2	-.1703229002E-03	.93061570E-04	-1.830	.0672	2366.4983
MARRIED	-.1051146481	.10276463	-1.023	.3064	.60997442
PARENT	-.8150219018	.11121645	-7.328	.0000	.38235294
CLUB	.2699389592E-01	.94469264E-01	.286	.7751	.23103154
FULLTIME	.1772640791	.98503984E-01	1.800	.0719	.34953112
DOGGY	.4264108636	.12657092	3.369	.0008	.10613811
N_O_HHM	.2611109966	.43030721E-01	6.068	.0000	2.6219096
INCOME3	-.4015464994	.99167482E-01	-4.049	.0001	.31500426
N_O_PV	.6912820176E-01	.68861958E-01	1.004	.3154	1.1423700
CAR_AVAI	.1043745339	.88931582E-01	1.174	.2405	.46376812
CITYCODE	-.9514576877E-01	.79630072E-01	-1.195	.2321	.57203751

Meet family or friends

```
+---------------------------------------------+
| Ordered Probability Model                   |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 11, 2005 at 10:16:46AM.|
| Dependent variable             INTERVAL     |
| Weighting variable                 None     |
| Number of observations             1670     |
| Iterations completed                 31     |
| Log likelihood function       -3386.850     |
| Restricted log likelihood     -3450.673     |
| Chi squared                    127.6464     |
| Degrees of freedom                   12     |
| Prob[ChiSqd > value] =         .0000000     |
| Underlying probabilities based on Logistic  |
|    Cell frequencies for outcomes            |
|  Y Count Freq  Y Count Freq  Y Count Freq    |
|  0   606 .362  1   292 .174  2   197 .117   |
|  3   133 .079  4   110 .065  5    75 .044   |
|  6    58 .034  7    33 .019  8    28 .016   |
|  9    33 .019 10    16 .009 11    18 .010   |
|   (cells 12-16 omitted)                     |
+---------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
	Index function for probability				
SEX	.1007103797	.99035777E-01	1.017	.3092	.48862275
AGE	.8567090024E-03	.93175799E-02	.092	.9267	33.072455
AGE2	.3033891223E-03	.12936552E-03	2.345	.0190	1436.8210
MARRIED	-.1966797716	.12860121	-1.529	.1262	.39640719
PARENT	.4773222822	.14579055	3.274	.0011	.20359281
CLUB	.9939383862E-01	.10170364	.977	.3284	.30419162
FULLTIME	.2249721789	.12207537	1.843	.0653	.27185629
DOGGY	.2658442579	.16556567	1.606	.1083	.82035928E-01
N_O_HHM	-.4672414026E-01	.49062008E-01	-.952	.3409	2.7958084
INCOME3	.2259436822	.12970583	1.742	.0815	.26407186
N_O_PV	.1124914052	.85693479E-01	1.313	.1893	1.2089820
CAR_AVAI	-.2904726532	.11271515	-2.577	.0100	.39940120
CITYCODE	.2560724688E-01	.87566733E-01	.292	.7700	.58203593

Club meeting

```
+---------------------------------------------+
| Ordered Probability Model                   |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 11, 2005 at 10:17:53AM.|
| Dependent variable             INTERVAL     |
| Weighting variable                 None     |
| Number of observations              448     |
| Iterations completed                 32     |
| Log likelihood function       -921.3009     |
| Restricted log likelihood     -935.8100     |
| Chi squared                    29.01818     |
| Degrees of freedom                   12     |
| Prob[ChiSqd > value] =         .3915579E-02 |
| Underlying probabilities based on Logistic  |
|    Cell frequencies for outcomes            |
|  Y Count Freq  Y Count Freq  Y Count Freq    |
|  0   108 .241  1    71 .158  2    53 .118    |
|  3    42 .093  4    24 .053  5    12 .026    |
|  6    95 .212  7     5 .011  8     1 .002    |
|  9     3 .006 10     5 .011 11     2 .004    |
|   (cells 12-16 omitted)                     |
+---------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
	Index function for probability				
SEX	.4254717439	.20300720	2.096	.0361	.47321429
AGE	.4183520267E-01	.24166754E-01	1.731	.0834	37.325893
AGE2	-.3614256161E-03	.30117271E-03	-1.200	.2301	1825.2321
MARRIED	-.1025305793E-01	.29294776	-.035	.9721	.47098214
PARENT	1.021456450	.32722570	3.122	.0018	.29241071
CLUB	-.3272802356E-01	.21497949	-.152	.8790	.39508929
FULLTIME	-.8096513516	.30461927	-2.658	.0079	.26339286
DOGGY	.5623159691	.31575361	1.781	.0749	.13169643
N_O_HHM	-.5325581036E-01	.95031170E-01	-.560	.5752	3.3013393
INCOME3	.6729059090	.34411191	1.955	.0505	.22544643
N_O_PV	.1595802031	.16704589	.955	.3394	1.2321429
CAR_AVAI	-1.019319283	.23935004	-4.259	.0000	.30803571
CITYCODE	.4446298698E-01	.22285284	.200	.8419	.70312500

Active sports

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+---------------------------------------------+
| Ordered Probability Model                   |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 11, 2005 at 10:18:34AM.|
| Dependent variable             INTERVAL     |
| Weighting variable                 None     |
| Number of observations              900     |
| Iterations completed                 34     |
| Log likelihood function       -1789.281     |
| Restricted log likelihood     -1841.858     |
| Chi squared                    105.1540     |
| Degrees of freedom                   12     |
| Prob[ChiSqd > value] =         .0000000     |
| Underlying probabilities based on Logistic  |
|    Cell frequencies for outcomes            |
|  Y Count Freq  Y Count Freq  Y Count Freq    |
|  0   294 .326  1   181 .201  2    82 .091   |
|  3    79 .087  4    43 .047  5    27 .030   |
|  6   102 .113  7    21 .023  8    11 .012   |
|  9     6 .006 10     5 .005 11    10 .011   |
|   (cells 12-16 omitted)                     |
+---------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
	Index function for probability				
SEX	-.2179421568	.13899584	-1.568	.1169	.57444444
AGE	.7897225927E-02	.17543437E-01	.450	.6526	32.248889
AGE2	.2287350261E-03	.23037604E-03	.993	.3208	1438.7911
MARRIED	-.2314662464	.21406802	-1.081	.2796	.42333333
PARENT	.1285338657	.20111888	.639	.5228	.28555556
CLUB	-.7278274042	.14851493	-4.901	.0000	.70111111
FULLTIME	-.4563911838E-02	.19353372	-.024	.9812	.30333333
DOGGY	.2358351261	.26269612	.898	.3693	.66666667E-01
N_O_HHM	.1748852743	.69513335E-01	2.516	.0119	3.2866667
INCOME3	.8584182065	.16910074	5.076	.0000	.21444444
N_O_PV	.3036746754	.11550010	2.629	.0086	1.3888889
CAR_AVAI	-.4269675453	.16336696	-2.614	.0090	.39000000
CITYCODE	-.2134874581	.13027612	-1.639	.1013	.67555556

Excursion into nature

```
+---------------------------------------------+
| Ordered Probability Model                   |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 11, 2005 at 10:19:27AM.|
| Dependent variable             INTERVAL     |
| Weighting variable                 None     |
| Number of observations               60     |
| Iterations completed                 32     |
| Log likelihood function       -145.7324     |
| Restricted log likelihood     -157.8479     |
| Chi squared                    24.23104     |
| Degrees of freedom                   12     |
| Prob[ChiSqd > value] =         .1891782E-01 |
| Underlying probabilities based on Logistic  |
|    Cell frequencies for outcomes            |
|  Y Count Freq  Y Count Freq  Y Count Freq    |
|  0     7 .116  1     8 .133  2     5 .083   |
|  3     2 .033  4     3 .050  5     7 .116   |
|  6     6 .100  7     4 .066  8     2 .033   |
|  9     2 .033 10     2 .033 11     2 .033   |
|   (cells 12-16 omitted)                     |
+---------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
	Index function for probability				
SEX	1.445347007	.72188487	2.002	.0453	.56666667
AGE	-.2207761977	.96797287E-01	-2.281	.0226	42.833333
AGE2	.2995325562E-02	.13066873E-02	2.292	.0219	2312.5667
MARRIED	.8584610262	.75456332	1.138	.2552	.38333333
PARENT	1.773879694	.93322000	1.901	.0573	.26666667
CLUB	-.9322133682E-01	.61350738	-.152	.8792	.38333333
FULLTIME	-2.475009005	1.0079903	-2.455	.0141	.23333333
DOGGY	2.308080878	1.4320960	1.612	.1070	.50000000E-01
N_O_HHM	1.189889889	.40526587	2.936	.0033	2.7833333
INCOME3	3.186554015	.84004946	3.793	.0001	.38333333
N_O_PV	-.6842879871	.76478394	-.895	.3709	1.0833333
CAR_AVAI	.5722469094	.83604472	.684	.4937	.43333333
CITYCODE	-.8633986213E-01	.75717239	-.114	.9092	.80000000

Stroll

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+---------------------------------------------+
| Ordered Probability Model                   |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 11, 2005 at 10:20:14AM.|
| Dependent variable             INTERVAL     |
| Weighting variable                 None     |
| Number of observations              883     |
| Iterations completed                 36     |
| Log likelihood function       -1104.400     |
| Restricted log likelihood     -1259.693     |
| Chi squared                    310.5848     |
| Degrees of freedom                   12     |
| Prob[ChiSqd > value] =         .0000000     |
| Underlying probabilities based on Logistic  |
|    Cell frequencies for outcomes            |
|  Y Count Freq  Y Count Freq  Y Count Freq    |
|  0   584 .661  1    73 .082  2    43 .048    |
|  3    33 .037  4    23 .026  5    27 .031    |
|  6    27 .031  7    17 .019  8     6 .006    |
|  9     4 .004 10     6 .006 11     9 .010    |
|   (cells 12-16 omitted)                     |
+---------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
	Index function for probability				
SEX	-.2179030540	.19173206	-1.136	.2557	.46885617
AGE	.4751894349E-01	.21605243E-01	2.199	.0278	39.602492
AGE2	-.3908127366E-03	.28698907E-03	-1.362	.1733	1856.4360
MARRIED	-.1941746157	.24708321	-.786	.4319	.66138165
PARENT	-1.099875158	.27273401	-4.033	.0001	.47338618
CLUB	.2897528853	.27267198	1.063	.2879	.11325028
FULLTIME	.4696750117	.21417560	2.193	.0283	.38052095
DOGGY	-2.248215532	.17087502	-13.157	.0000	.71460929
N_O_HHM	.9753580630E-01	.89089065E-01	1.095	.2736	2.9773499
INCOME3	-1.161692776	.26726978	-4.347	.0000	.21291053
N_O_PV	-.3061845730E-01	.18927235	-.162	.8715	1.1177803
CAR_AVAI	.9636575226E-01	.22191525	.434	.6641	.34541336
CITYCODE	.8941793472	.20421944	4.379	.0000	.20498301

Going out (bar, restaurant etc.)

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+---------------------------------------------+
| Ordered Probability Model                   |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 11, 2005 at 10:20:46AM.|
| Dependent variable             INTERVAL     |
| Weighting variable                 None     |
| Number of observations              800     |
| Iterations completed                 32     |
| Log likelihood function       -1765.662     |
| Restricted log likelihood     -1799.567     |
| Chi squared                    67.81037     |
| Degrees of freedom                   12     |
| Prob[ChiSqd > value] =         .0000000     |
| Underlying probabilities based on Logistic  |
|    Cell frequencies for outcomes            |
|  Y Count Freq  Y Count Freq  Y Count Freq    |
|  0   250 .313  1   113 .142  2    89 .111    |
|  3    56 .070  4    44 .055  5    45 .056    |
|  6    62 .077  7    37 .046  8    19 .023    |
|  9    17 .021 10    11 .013 11    17 .021    |
|   (cells 12-16 omitted)                     |
+---------------------------------------------+
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Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
	Index function for probability				
SEX	-.9341076139E-01	.15339643	-.609	.5426	.50750000
AGE	.5131249992E-01	.13750981E-01	3.732	.0002	38.328750
AGE2	-.3841170826E-03	.17910116E-03	-2.145	.0320	1774.7438
MARRIED	-.4362269299	.18278189	-2.387	.0170	.46000000
PARENT	-.3729729533	.18544851	-2.011	.0443	.29250000
CLUB	-.1871538852	.13690998	-1.367	.1716	.35750000
FULLTIME	-.2318586665	.17610548	-1.317	.1880	.45875000
DOGGY	.5650674003	.31098319	1.817	.0692	.52500000E-01
N_O_HHM	.2095869250	.71609004E-01	2.927	.0034	2.5350000
INCOME3	-.5121768353E-01	.17869212	-.287	.7744	.38125000
N_O_PV	.5897239918E-01	.10990252	.537	.5916	1.2775000
CAR_AVAI	-.7104927542	.14956383	-4.750	.0000	.55000000
CITYCODE	-.1735025215	.14591378	-1.189	.2344	.71250000

Thurgau

Daily shopping

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+---------------------------------------------+
| Ordered Probability Model                   |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 10, 2005 at 06:23:45PM.|
| Dependent variable             INTERVAL     |
| Weighting variable                 None     |
| Number of observations             1526     |
| Iterations completed                 31     |
| Log likelihood function       -2936.598     |
| Restricted log likelihood     -2987.448     |
| Chi squared                    101.7004     |
| Degrees of freedom                   12     |
| Prob[ChiSqd > value] =         .0000000     |
| Underlying probabilities based on Logistic  |
|    Cell frequencies for outcomes            |
|  Y Count Freq  Y Count Freq  Y Count Freq    |
|  0   530 .347  1   318 .208  2   208 .136   |
|  3   123 .081  4    72 .047  5    69 .045   |
|  6    93 .060  7    26 .017  8    23 .015   |
|  9     8 .005 10     8 .005 11     5 .003   |
|   (cells 12-16 omitted)                     |
+---------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
	Index function for probability				
SEX	.4307708861	.11258276	3.826	.0001	.35386632
AGE	-.1582977327E-01	.10945995E-01	-1.446	.1481	47.804063
AGE2	.1526240513E-03	.13415466E-03	1.138	.2553	2503.8866
PARTNER	.5495174676E-01	.12687644	.433	.6649	.74836173
PARENT	-.8074812600	.16347461	-4.939	.0000	.25491481
CLUB	-.2953644776	.10393759	-2.842	.0045	.45085190
FULLTIME	.7541850396	.12059886	6.254	.0000	.40498034
DOGGY	-.1436705607E-01	.13719478	-.105	.9166	.15203145
N_O_HHM	.3136061592	.61787031E-01	5.076	.0000	2.5714286
INCOME3	-.3201973153	.11099709	-2.885	.0039	.69397117
N_O_V	-.5929711723E-02	.39839040E-01	-.149	.8817	1.7496723
CAR_AVAI	.4140656240	.15753559	2.628	.0086	.85321101
AGGLO	-.9253007224E-01	.10747845	-.861	.3893	.59436435

Longterm shopping

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+---------------------------------------------+
| Ordered Probability Model                   |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 10, 2005 at 06:26:13PM.|
| Dependent variable             INTERVAL     |
| Weighting variable                 None     |
| Number of observations              561     |
| Iterations completed                 31     |
| Log likelihood function       -1368.474     |
| Restricted log likelihood     -1381.138     |
| Chi squared                    25.32941     |
| Degrees of freedom                   12     |
| Prob[ChiSqd > value] =         .1333678E-01 |
| Underlying probabilities based on Logistic  |
|    Cell frequencies for outcomes            |
|  Y Count Freq  Y Count Freq  Y Count Freq    |
|  0   102 .181  1    82 .146  2    60 .106    |
|  3    57 .101  4    48 .085  5    41 .073    |
|  6    52 .092  7    20 .035  8    21 .037    |
|  9    19 .033 10    14 .024 11    11 .019    |
|   (cells 12-16 omitted)                     |
+---------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
	Index function for probability				
SEX	.1155495615	.17807716	.649	.5164	.35294118
AGE	.4868810893E-01	.21410233E-01	2.274	.0230	42.843137
AGE2	-.3638539371E-03	.26469854E-03	-1.375	.1693	2086.1194
PARTNER	-.5675579667	.23142670	-2.452	.0142	.78609626
PARENT	-.9548366549	.21856962	-4.369	.0000	.38324421
CLUB	-.4693279258E-02	.15922114	-.029	.9765	.48841355
FULLTIME	.4137355846	.17977174	2.301	.0214	.51158645
DOGGY	.3247821523	.23944826	1.356	.1750	.12834225
N_O_HHM	.2767113980	.76052976E-01	3.638	.0003	3.1069519
INCOME3	-.3058183361	.18646244	-1.640	.1010	.59180036
N_O_V	-.4863629291E-01	.62127744E-01	-.783	.4337	2.0249554
CAR_AVAI	.1115314503	.29639037	.376	.7067	.85739750
AGGLO	.1262720449	.16059710	.786	.4317	.45098039

Private business

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+---------------------------------------------+
| Ordered Probability Model                   |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 10, 2005 at 06:27:38PM.|
| Dependent variable             INTERVAL     |
| Weighting variable                 None     |
| Number of observations             1135     |
| Iterations completed                 31     |
| Log likelihood function       -2251.215     |
| Restricted log likelihood     -2273.863     |
| Chi squared                    45.29595     |
| Degrees of freedom                   12     |
| Prob[ChiSqd > value] =         .9167996E-05 |
| Underlying probabilities based on Logistic  |
|    Cell frequencies for outcomes            |
|  Y Count Freq  Y Count Freq  Y Count Freq    |
|  0   402 .355  1   222 .195  2   141 .124   |
|  3    85 .074  4    70 .061  5    56 .049   |
|  6    60 .052  7    24 .021  8    13 .011   |
|  9    15 .013 10     9 .007 11     3 .002   |
|   (cells 12-16 omitted)                     |
+---------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
	Index function for probability				
SEX	.5890711251E-01	.13766837	.428	.6687	.46519824
AGE	-.2973077248E-03	.14943283E-01	-.020	.9841	49.187665
AGE2	.6178970346E-04	.17787115E-03	.347	.7283	2597.4626
PARTNER	.1029049583	.14677166	.701	.4832	.75682819
PARENT	-.2812216440	.20508417	-1.371	.1703	.27929515
CLUB	-.4709500228	.11841567	-3.977	.0001	.49339207
FULLTIME	.4003409480	.14636945	2.735	.0062	.48281938
DOGGY	-.1458268082	.15847659	-.920	.3575	.15066079
N_O_HHM	.7448726159E-01	.76706961E-01	.971	.3315	2.5136564
INCOME3	-.3503140716	.14283423	-2.453	.0142	.69162996
N_O_V	.1821975819E-01	.49618668E-01	.367	.7135	1.7612335
CAR_AVAI	.5515813163	.23422383	2.355	.0185	.91718062
AGGLO	.5771672078E-01	.11947540	.483	.6290	.51189427

Meeting family or friends

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+---------------------------------------------+
| Ordered Probability Model                   |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 10, 2005 at 06:29:42PM.|
| Dependent variable             INTERVAL     |
| Weighting variable                 None     |
| Number of observations             1035     |
| Iterations completed                 32     |
| Log likelihood function       -2267.687     |
| Restricted log likelihood     -2302.516     |
| Chi squared                    69.65865     |
| Degrees of freedom                   12     |
| Prob[ChiSqd > value] =         .0000000     |
| Underlying probabilities based on Logistic  |
|    Cell frequencies for outcomes            |
|  Y Count Freq  Y Count Freq  Y Count Freq    |
|  0   344 .332  1   142 .137  2   118 .114   |
|  3    75 .072  4    63 .060  5    73 .070   |
|  6    52 .050  7    26 .025  8    14 .013   |
|  9    17 .016 10    24 .023 11    15 .014   |
|   (cells 12-16 omitted)                     |
+---------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
	Index function for probability				
SEX	.1660126103	.12535832	1.324	.1854	.41932367
AGE	.2874170428E-01	.18079111E-01	1.590	.1119	36.800000
AGE2	-.2438751237E-03	.23251798E-03	-1.049	.2942	1698.4232
PARTNER	.1110661624	.14509439	.765	.4440	.58067633
PARENT	.2956690725	.20031751	1.476	.1399	.14396135
CLUB	-.1649181122	.12190820	-1.353	.1761	.52077295
FULLTIME	.1618004605E-01	.15473739	.105	.9167	.57584541
DOGGY	.1422250922	.19498739	.729	.4658	.10628019
N_O_HHM	.1938416974	.52583527E-01	3.686	.0002	2.8135266
INCOME3	-.6400631480E-02	.13981972	-.046	.9635	.58937198
N_O_V	-.1231539527	.51566805E-01	-2.388	.0169	2.0231884
CAR_AVAI	-.6235836411	.24090599	-2.588	.0096	.74299517
AGGLO	.3982980124	.13393885	2.974	.0029	.43381643

Club meeting

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+---------------------------------------------+
| Ordered Probability Model                   |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 10, 2005 at 06:49:55PM.|
| Dependent variable             INTERVAL     |
| Weighting variable                 None     |
| Number of observations              609     |
| Iterations completed                 32     |
| Log likelihood function       -1313.435     |
| Restricted log likelihood     -1323.126     |
| Chi squared                    19.38296     |
| Degrees of freedom                   12     |
| Prob[ChiSqd > value] =         .7969616E-01 |
| Underlying probabilities based on Logistic  |
|    Cell frequencies for outcomes            |
|  Y Count Freq  Y Count Freq  Y Count Freq    |
|  0   128 .210  1   114 .187  2    78 .128    |
|  3    50 .082  4    53 .087  5    40 .065    |
|  6    92 .151  7    14 .022  8     5 .008    |
|  9     6 .009 10     2 .003 11     3 .004    |
|   (cells 12-16 omitted)                     |
+---------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
	Index function for probability				
SEX	.1026163835	.15473998	.663	.5072	.47783251
AGE	.2880869891E-01	.28286666E-01	1.018	.3085	35.328407
AGE2	-.7307341049E-04	.31843883E-03	-.229	.8185	1620.7504
PARTNER	-1.004623227	.33920851	-2.962	.0031	.59441708
PARENT	-.2164795971	.23594709	-.917	.3589	.19540230
CLUB	-.4390941930	.20053914	-2.190	.0286	.74384236
FULLTIME	.1618960324	.16769146	.965	.3343	.50738916
DOGGY	.7964455851	.30805297	2.585	.0097	.64039409E-01
N_O_HHM	.3378411612	.87337352E-01	3.868	.0001	3.4614122
INCOME3	-.2386210956	.16679268	-1.431	.1525	.57963875
N_O_V	-.7861933660E-01	.55200924E-01	-1.424	.1544	2.3875205
CAR_AVAI	.6884978941	.44826681	1.536	.1246	.64696223
AGGLO	-.2079966350	.15861922	-1.311	.1898	.45320197

Active sports

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+---------------------------------------------+
| Ordered Probability Model                   |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 10, 2005 at 06:51:50PM.|
| Dependent variable             INTERVAL     |
| Weighting variable                 None     |
| Number of observations              859     |
| Iterations completed                 32     |
| Log likelihood function       -1717.620     |
| Restricted log likelihood     -1757.772     |
| Chi squared                    80.30327     |
| Degrees of freedom                   12     |
| Prob[ChiSqd > value] =         .0000000     |
| Underlying probabilities based on Logistic  |
|    Cell frequencies for outcomes            |
|  Y Count Freq  Y Count Freq  Y Count Freq    |
|  0   252 .294  1   163 .189  2   114 .132   |
|  3    89 .103  4    30 .034  5    36 .041   |
|  6   104 .121  7    10 .011  8     9 .010   |
|  9    15 .017 10     6 .006 11     3 .003   |
|   (cells 12-16 omitted)                     |
+---------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
	Index function for probability				
SEX	.1147410416	.13813369	.831	.4062	.50523865
AGE	-.6290853495E-02	.20903011E-01	-.301	.7634	37.071013
AGE2	-.4694010860E-04	.23892848E-03	-.196	.8442	1779.0710
PARTNER	.5821312790	.20404585	2.853	.0043	.53550640
PARENT	-.4114023662	.19390850	-2.122	.0339	.20256112
CLUB	.5163183240	.14850310	3.477	.0005	.62863795
FULLTIME	.1841677425	.14435678	1.276	.2020	.48894063
DOGGY	1.260229251	.25436858	4.954	.0000	.71012806E-01
N_O_HHM	.1016401894	.56290948E-01	1.806	.0710	3.3678696
INCOME3	-.2947219329	.18098771	-1.628	.1034	.61583236
N_O_V	.7718306875E-01	.50148812E-01	1.539	.1238	2.0686845
CAR_AVAI	.2996258323	.23157459	1.294	.1957	.64726426
AGGLO	-.1009910085	.15508749	-.651	.5149	.55064028

Excursion into nature

```
+---------------------------------------------+
| Ordered Probability Model                   |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 10, 2005 at 06:54:21PM.|
| Dependent variable             INTERVAL     |
| Weighting variable                 None     |
| Number of observations              320     |
| Iterations completed                 31     |
| Log likelihood function       -601.1690     |
| Restricted log likelihood     -611.7151     |
| Chi squared                    21.09236     |
| Degrees of freedom                   12     |
| Prob[ChiSqd > value] =         .4904423E-01 |
| Underlying probabilities based on Logistic  |
|    Cell frequencies for outcomes            |
|  Y Count Freq  Y Count Freq  Y Count Freq    |
|  0   147 .459  1    49 .153  2    16 .050    |
|  3    19 .059  4    14 .043  5    14 .043    |
|  6    23 .071  7     8 .025  8     4 .012    |
|  9     3 .009 10     7 .021 11     7 .021    |
|   (cells 12-15 omitted)                     |
+---------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
	Index function for probability				
SEX	.1568856322	.26072204	.602	.5474	.64062500
AGE	.4705384678E-01	.32640705E-01	1.442	.1494	49.475000
AGE2	-.3840766170E-03	.41661724E-03	-.922	.3566	2770.8000
PARTNER	-1.477769664	.46633396	-3.169	.0015	.79375000
PARENT	.1443418914	.35400168	.408	.6835	.21250000
CLUB	-.2492157107	.24779032	-1.006	.3145	.43750000
FULLTIME	-.5580821674E-01	.26545202	-.210	.8335	.48750000
DOGGY	.1425229496	.32208608	.442	.6581	.13125000
N_O_HHM	.1118924188	.13956876	.802	.4227	2.7156250
INCOME3	-.3636057783	.25268465	-1.439	.1502	.69375000
N_O_V	-.2439700982	.13861905	-1.760	.0784	1.3343750
CAR_AVAI	.5074958186	.39197588	1.295	.1954	.73125000
AGGLO	-.2988988490E-01	.32752604	-.091	.9273	.72812500

Stroll

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+---------------------------------------------+
| Ordered Probability Model                   |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 10, 2005 at 06:18:44PM.
| Dependent variable             INTERVAL     |
| Weighting variable                 None     |
| Number of observations              781     |
| Iterations completed                 36     |
| Log likelihood function       -1119.076     |
| Restricted log likelihood     -1261.172     |
| Chi squared                    284.1912     |
| Degrees of freedom                   12     |
| Prob[ChiSqd > value] =         .0000000     |
| Underlying probabilities based on Logistic  |
|    Cell frequencies for outcomes            |
|  Y Count Freq  Y Count Freq  Y Count Freq    |
|  0   448 .573  1   101 .129  2    44 .056    |
|  3    42 .053  4    26 .033  5    26 .033    |
|  6    37 .047  7    11 .014  8     8 .010    |
|  9     6 .007 10     5 .006 11     7 .008    |
|   (cells 12-16 omitted)                     |
+---------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
	Index function for probability				
SEX	.2301984964	.20184155	1.140	.2541	.48399488
AGE	.7362814797E-01	.26644712E-01	2.763	.0057	45.585147
AGE2	-.9443662990E-03	.31953237E-03	-2.955	.0031	2326.6940
PARTNER	-.8130153958	.25608791	-3.175	.0015	.79385403
PARENT	.7033539720E-01	.23507786	.299	.7648	.26632522
CLUB	-.4421262623	.16782694	-2.634	.0084	.43021767
FULLTIME	.1255693410	.19514559	.643	.5199	.46606914
DOGGY	-2.462195185	.16620245	-14.814	.0000	.70166453
N_O_HHM	.3238343970	.81629011E-01	3.967	.0001	2.9551857
INCOME3	-.7366743588E-01	.18182650	-.405	.6854	.71959027
N_O_V	-.1872284083E-01	.75839278E-01	-.247	.8050	2.0268886
CAR_AVAI	-.1147346012	.42003389	-.273	.7847	.88732394
AGGLO	.4192120798	.16619775	2.522	.0117	.35851472

Going out (bar, restaurant etc.)

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+---------------------------------------------+
| Ordered Probability Model                   |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 10, 2005 at 06:55:36PM.|
| Dependent variable             INTERVAL     |
| Weighting variable                 None     |
| Number of observations             1102     |
| Iterations completed                 33     |
| Log likelihood function       -2079.171     |
| Restricted log likelihood     -2138.663     |
| Chi squared                    118.9833     |
| Degrees of freedom                   12     |
| Prob[ChiSqd > value] =         .0000000     |
| Underlying probabilities based on Logistic  |
|    Cell frequencies for outcomes            |
|  Y Count Freq  Y Count Freq  Y Count Freq    |
|  0   480 .435  1   155 .140  2   119 .107   |
|  3    69 .062  4    45 .040  5    62 .056   |
|  6    61 .055  7    24 .021  8    19 .017   |
|  9    17 .015 10    13 .011 11    14 .012   |
|   (cells 12-16 omitted)                     |
+---------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
	Index function for probability				
SEX	-.2973753546	.13657201	-2.177	.0294	.59346642
AGE	-.6074220616E-02	.16719557E-01	-.363	.7164	40.958258
AGE2	.9287485736E-04	.20839189E-03	.446	.6558	1915.1361
PARTNER	-.1252555024	.14865005	-.843	.3994	.71960073
PARENT	.2530161511	.18319698	1.381	.1672	.22595281
CLUB	.2029418773	.11732272	1.730	.0837	.55353902
FULLTIME	-.4177095891E-01	.15984519	-.261	.7938	.67695100
DOGGY	.4346824099	.21498060	2.022	.0432	.84392015E-01
N_O_HHM	.3300056474	.63288136E-01	5.214	.0000	2.6315789
INCOME3	.4453510559	.14940353	2.981	.0029	.63974592
N_O_V	-.5387817223E-01	.68361415E-01	-.788	.4306	1.7513612
CAR_AVAI	-.8303034381	.23144206	-3.588	.0003	.86842105
AGGLO	.2763727559	.12689679	2.178	.0294	.47096189

A 7 Curriculum Vitae

Name:	Stefan Schönfelder
Date of birth:	19 May 1973
Place of birth:	Wolfenbüttel/Germany
Marital status:	Married

Job history:

Since January 2006:	Consultant, Trafico/Vienna
July 1999 – August 2005:	Research assistant, Institute for Transport Planning and Systems (IVT), Swiss Federal Institute of Technology Zürich (ETH)

Research foci at the IVT:	Analysis and modelling of regularities and spatial choice in travel behaviour
Research projects at the IVT:	Mobi*drive* – Dynamik und Routinen im Verkehrshalten (1999-2001; funding body: German Federal Ministry of Research and Education)
	Mobiplan – Eigene Mobilität verstehen und planen (1999-2001; funding body: German Federal Ministry of Research and Education)
	Structure and use of human activity spaces (2002-2004; funding body: Department BAUG, Swiss Federal Institute of Technology)
	Stabilität des Verkehrsverhaltens (2003-2004; funding body: SVI)
Education:	Abitur 1992 – Gymnasium im Schloss, Wolfenbüttel
	Diplom 1999 (Diplom-Ingenieur Raumplanung) – Universität Dortmund, Dortmund

Publications:

Peer reviewed journal articles:

Wolf, J., S. Schönfelder, U. Samaga, M. Oliveira and K.W. Axhausen (2004) 80 weeks of GPS-traces: Approaches to enriching the trip information, *Transportation Research Record,* **1870**, 46-54.

Schlich, R., S. Schönfelder, S. Hanson and K.W. Axhausen (2004) Structures of leisure travel: Temporal and spatial variability, *Transport Reviews*, **24** (2) 219-238

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Book sections and contributions to conference proceedings:

Schönfelder, S. and K.W. Axhausen (2003) On the variability of human activity spaces, in M. Koll-Schretzenmayr, M. Keiner and G. Nussbaumer (eds.) *The Real and Virtual Worlds of Spatial Planning*, 237-262, Springer, Heidelberg.

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Schönfelder, S. and K.W. Axhausen (2001) Mobidrive - Längsschnitterhebungen zum individuellen Verkehrsverhalten: Perspektiven für raum-zeitliche Analysen, in M. Schrenk (ed.) *Proceedings of CORP 2001*, **2**, 315-321, Technische Universität Wien, Wien.

Schönfelder, S. and K.W. Axhausen (2000) Periodizität im Verkehrsverhalten: Erste Ergebnisse mit Überlebenszeitmodellen, *Stadt Region Land*, **69**, 131-144.

Working and conference papers; reports:

Schönfelder, S., J.H. Rich, O.A. Nielsen, C. Würtz and K.W. Axhausen (2005) Road pricing and its individual responses within travel patterns – lessons from the AKTA study, paper presented at the *European Transport Conference 2005*, Strasbourg, October 2005.

Schönfelder, S., H. Li, R. Guensler, J. Ogle and K.W. Axhausen (2005) Analysis of Commute Atlanta Vehicle Instrumented GPS data: Destination Choice Behavior and Activity Spaces, *Arbeitsberichte Verkehrs- und Raumplanung*, **303**, IVT, ETH, Zürich.

Löchl, M., S. Schönfelder, R. Schlich, T. Buhl, P. Widmer and K.W. Axhausen (2005) Stabilität des Verkehrsverhaltens, final report, SVI 2001/514, *Schriftenreihe*, **1120**, Bundesamt für Strassen, UVEK, Bern.

Vaze, V.S., S. Schönfelder and K.W. Axhausen (2005) Continuous space representations of human activity spaces, *Arbeitsberichte Verkehrs- und Raumplanung*, **295**, IVT, ETH, Zürich.

Schönfelder, S. and K.W. Axhausen (2004) Structure and innovation of human activity spaces, *Arbeitsberichte Verkehrs- und Raumplanung*, **258**, IVT, ETH Zürich, Zürich.

Schönfelder, S. (2003) Between routines and variety seeking: The characteristics of locational choice in daily travel, paper presented at the *10th International Conference on Travel Behaviour Research*, Lucerne, August 2003.

Schönfelder, S. and U. Samaga (2003) Where do you want to go today? - More observations on daily mobility, *Arbeitsberichte Verkehrs- und Raumplanung*, **179**, IVT, ETH, Zürich.

Presentations:

Schönfelder, S. (2005) IKT/Handel/Verkehr – Die Sicht der Verkehrsverhaltensforschung, Presentation at Vi-Va Workshop, Berlin, April 2005.

Schönfelder, S. (2005) Stability and innovation of human activity spaces, Presentation at GeorgiaTech, Atlanta, January 2005.

Schönfelder, S. (2003) Activity space: Concept, measurement and first results, Presentation at the Danish Technical University, Copenhagen, June 2003.

Schönfelder, S. (2003) Alttagsmobilität - Aktivitätenräume, Presentation at Lehrstuhl für Verkehrsökologie, Technische Universität Dresden, May 2003.

Schönfelder, S. (2001) ... things people do in time and space - Untersuchungen zur Alltagsmobilität, Presentation at IRPUD Forschungskolloquium, Dortmund, July 2001.

Schönfelder, S . (2001) Some notes on space, location and travel behaviour, Presentation at *1st Swiss Transport Research Conference*, Ascona, March 2001.