STABILITY AND FLEXIBILITY IN COMMUTING BEHAVIOR – ANALYSES OF MODE CHOICE PATTERNS IN GERMANY

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ABSTRACT

Daily travel behavior varies within one week: Individuals perform different activities and may use different modes. Considering the working population in Germany, 39% of their trips are work-related. Since these trips cover large parts of daily travel behavior, decisions on commuting mode choice and variation influence the transportation system in general; they are relevant to assess infrastructure needs and design mobility management concepts. Based on the German Mobility Panel, a one week national household travel survey, we analyzed whether and how commuting mode choice patterns vary on the individual level and which factors influence this variation. Since the occurrence of additional activities on the way from home to work and back may influence individual mode choice, we did not consider working trips only but the whole commuting tour. To consider various factors of stability and flexibility in commuting behavior, we used a multinomial logistic regression model. Our analyses show that 58% of the commuters integrate additional activities at least once a week and 27% use several different modes for commuting within the week. Our logistic regression results indicate that commuting mode choice and mode variation is determined by several factors like socio-demographics, commuting tour characteristics, the availability of cars and transit passes and transportation system based factors (e.g. parking pressure). Our results may help employers to reflect flexibility of the employees by providing an infrastructure that enables multimodal behavior. Influencing factors for commuting mode choice may be a valuable help to forecast and steer demands, e.g. by promoting transit passes for employees.

INTRODUCTION

Commuting-related trips are important trips in daily travel behavior, especially for employed persons. In Germany 39% of all trips of employed persons are work-related. I.e. work-related trips do not only cover direct trips to work but also other trips done on the tour from home to work and back. Since these trips are a significant part of general travel behavior, commuting mode choice decisions are important to be investigated.

Our work examines the stability and flexibility in commuting behavior in terms of mode choice. To reflect variations in mode choice and thus multimodal commuting behavior, we investigate data from a longitudinal perspective using the data of the German Mobility Panel, a one week national household travel survey. In our approach, we consider travel behavior during a week and thus the intrapersonal variability and stability of commuting mode choice. Furthermore, we do not only analyze work-related trips but aggregate the trips to tours from home to work and back, including additional activities on these tours. This enables us to compare mode choice behavior in relation to the integrated activities within a commuting tour and to identify drivers and motivations of changing mode usage due to other activities before or after work. The integration of activities seems to be an important aspect on mode stability and flexibility but is still only one of various factors influencing commuting mode choice. In order to quantify the different aspects of individual mode choice patterns, we use a multinomial logistic regression model.

The insights gained by our work might help employers to design a mobility management concept and to provide a suitable amount of transportation facilities for employees related to their multimodal commuting behavior: How many parking spaces for cars and bicycles are needed? In what situations do persons need what kind of transportation supply? What kind of commuters or persons need what kind of facility and how often during a week? What are factors to influence mode choice that can be triggered by employers?

The paper is organized as follows: First we review relevant studies on commuting mode choice. Second the dataset of the German Mobility Panel is described followed by an outline of methods used for the descriptive analyses and the logit estimation. The remaining chapters show the results and draw a final conclusion.

LITERATURE REVIEW

Commuting behavior, especially mode choice, is much discussed in travel behavior literature. Various studies were conducted either on a local or on a national level both for developed countries or regions such as the United States (*1–8*), Canada (*9*), Great Britain (*10*), Ireland (*11*), the Netherlands (*12–16*) and Spain (*17*) and for less developed countries, e.g. Vietnam (*18*) and China (*19*). Most studies investigated general commuting mode choice behavior by analyzing one-day trip diaries (*20; 2; 11; 7*) or surveys with general questions on commuting behavior (*4; 6–8; 18; 21*). However, there is little knowledge about the variation of commuting mode choice within longer periods. The general variation of mode choice was discussed by various authors, e.g. Kitamura (*22*), Hansen & Huff (*23*) and Kuhnimhof et al. (*24*). According to our knowledge Heinen et al. (*13*) were the only authors who analyzed day-to-day variation on commuting mode choice using a longitudinal internet survey among commuters in the Delft area. They focused on commuting with bicycles and established a model which indicates full-time and part-time cycling commuters using a logistic regression model.

Many authors used logistic regression models for their analyses (e.g. *11; 7; 8*). Other methods such as random coefficient analyses (*13*) or t-tests (*4; 16*) were also utilized. The factors discussed in scientific literature impacting commuting mode choice can be mainly summarized to four categories: socio-demographic attributes, personal facilities, infrastructure supply based factors and commuting trip characteristics. Various studies reported that commuting mode choice depends on socio-economic factors such as age, gender, household size, household income and education, e.g. (*20; 11; 21*). The availability of personal facilities such as a car, a bicycle or a transit pass has an additional impact on commuting mode choice, e.g. (*1; 9; 18*). Furthermore, the transportation supply and infrastructure both at the place of living and at the place of work have an impact such as car and bicycle parking possibilities and the existence of nearby public transportation stations, e.g. (*4; 5; 7*). The characteristics of the commuting trips such as trip length and trip duration, trip cost and weather conditions were identified by most authors as relevant influence factors, e.g. (*2; 13; 10*). Frank et al. (*3*), Ho & Mulley (*25*), Krygsman et al. (*15*), and others studied whether additional activities on commuting tours such as service or shopping activities might influence commuting mode choice using one-day survey data. However, it was not yet discussed whether the occurrence of additional activities on commuting tours affects the commuting mode variation within one week. Our work aims at generating additional knowledge about commuting travel behavior by answering the following questions: Does an individual day-to-day variation on commuting mode choice exist? Can the variation in commuting mode choice partly be explained by the occurrence of additional activities on commuting tours?

DATA

We used the data of the German Mobility Panel (MOP) for our analyses. Since 1994 the MOP annually collects data about the travel behavior of the German population. Every year approximately 1,000-1,500 households with 2,000-2,400 persons (aged ten years and older) contribute to the MOP survey by filling in a trip diary for one week. The MOP survey takes place in autumn every year and the weeks are chosen not to contain any holidays ("everyday travel"). The survey is carried out on behalf of and funded by the German Federal Ministry of Transport and Digital Infrastructure. The Institute for Transport Studies of the Karlsruhe Institute of Technology (KIT) is responsible for the design and scientific supervision of the survey (*26; 27*). The participants provide a complete trip diary containing information about all their trips during a whole week, i.e. distances, means of transportation used, purposes and start resp. arrival times. Moreover, socio-demographic information about the survey participants (e.g. status of employment, gender, age), the availability of cars, bicycles and e.g. transit passes as well as certain characteristics of the transportation system facilities (e.g. car park availability at home and at work, transit service quality for commuting). Moreover, the survey participants report every day within the survey period whether it was a rather normal or a particular day, i.e. the participant was ill, on vacation or the car was under repair.

For our work on commuting mode choice we cut the sample in order to ensure that only commuting behavior in everyday travel is represented. Only persons aged 18 and older who are employed full time or part time and who did not report any particularity (i.e. they were not ill or on holiday) during the survey period were included in the analyses. Thus school related trips are not included. The dataset is based on the data collected between 2004 and 2013; the gross sample includes 5,011 persons with a total of more than 140,000 reported trips. We pool data of the different years and regard repeated survey participants as independent.

METHODS

In order to understand the variation of mode choice behavior for commuting better, we made a descriptive and a regression analysis to identify relevant influencing factors. Therefore, we identified commuting tours out of the trip diaries, grouped the commuters according to their commuting behavior and utilized a logistic regression model. Our approach is described in the following sections.

Identification of Commuting Tours (Tour Level)

To estimate commuting attributes of persons, we first determined elements of the travel behavior that include commuting. Therefore, we aggregated trips to chains and then chains to tours. On the first aggregation level, we grouped trips and examined two types of trip-chains: chains from home to work and chains from work back home. Chains can consist of one direct trip to work only or of several trips, e.g. integrating a shopping activity from home to work. On the second aggregation level we connected one chain from home to work with the respective chain back home to one tour, because mode decision between these two types of chains are highly dependent from each other (e.g. taking the car on the first chain usually implies taking the car on the return chain). We call these tours commuting tours. To evaluate commuting attributes on the tour level, we defined some characteristics of the tours, e.g. the main mode used or the occurrence of additional activities like shopping, leisure or service (pick-up and drop-off).

Identification of Commuting Attributes per Person (Individual Level)

By using survey data of a whole week we were able not only to consider the tour level but also the potentially varying commuting behavior on the individual level. To do this, we considered all commuting tours within the whole week. By aggregating the tours we identified commuting behavior of persons.

First we distinguished persons by the activities they integrate into their commuting tours. This resulted in five groups (*activity based* commuting behavior type):

Persons who …

- … have direct commuting tours only.
- … integrate shopping activities only.
- … integrate leisure activities only.
- … integrate service activities only.
- … integrate several different activities.

Second, we distinguished persons by their modal behavior for commuting. We defined a main mode for every person in the sample as the mode with the highest number of uses (occurrences). Subsequently we grouped the persons into ten groups (*mode based* commuting behavior type):

Persons who …

- … always commute *walking*.
- … mainly commute *walking* but also by other modes.
- … always commute by *bicycle*.
- … mainly commute by *bicycle* but also by other modes.
- … always commute by *car as driver*.
- … mainly commute by *car as driver* but also by other modes.
- … always commute by *car as passenger*.
- … mainly commute by *car as passenger* but also by other modes.
- … always commute by *public transportation*.
- … mainly commute by *public transportation* but also by other modes.

This definition allows for a more detailed analysis why there is a variation in mode and which factors have a relevant influence.

Logit Estimation Week Context

In our approach we combine two aspects: Our findings show that a certain proportion of commuters varies the commuting mode during the survey week (multimodal commuting behavior). Literature reveals that the general commuting mode choice is influenced by certain factors. We aimed at explaining which factors influence mode choice and mode variation on an individual level. Therefore, we estimated a multinomial logit model. We pooled potential factors into four groups: Socio-demographic characteristics, the availability of cars, bicycles and transit passes, commuting tour characteristics (e.g. integration of additional activities) and transportation system facility based factors (e.g. parking situation).

For the estimation, the software tools SAS and NLOGIT were used. The dependent variable for the logistic regression model was the mode based commuting behavior type, introduced in the last section. *Car as driver* is the dominant type and was therefore used as reference category.

RESULTS

The methods used enable us to present results both on tour and individual level. Therefore we first show results on tour level and then considering the individual mode choice patterns and the influence factors on these patterns estimating and presenting the results of the logistic regression model.

Characterization of Commuting Tours

On tour level, we examine all identified tours to show their complexity and to describe the tour based modal split. The following table shows the most frequent commuting tour types occurred in the data.

TABLE 1 Most Frequent Commuting Tour Types

Tour Type		Share of all tours [%]
direct tour	H - W - H	72.7%
integrates shopping in the return chain	H - W - SH - H	9.2%
integrates leisure in the return chain	H - W - L - H	4.4%
integrates service in the first chain	H - SE - W - H	2.6%
integrates shopping in the first chain	H - SH - W - H	1.8%
integrates service in both chains	H - SE - W - SE - H	1.3%
integrates service in the return chain	H - W - SE - H	1.2%
integrates leisure in the first chain	H - L - W - H	1.0%
integrates shopping and leisure in the return chain	H - L - SH/L - H	1.0%
other		5.0%

H=Home, W=Work, L=Leisure, SH=Shopping, SE=Service

TABLE 1 shows the shares of the different tour types. 73% of the tours are direct tours, integrating no other activity. Nevertheless, about 27% of all tours contain additional activities. Most often a shopping activity in the return chain is included, i.e. on the way from the working place to home, followed by the integration of a leisure activity in the return chain. The analysis shows that persons integrate additional activities on more than a quarter of all tours. This indicates that the occurrence of additional activities needs to be considered when examining mode choice since they affect tour characteristics like tour distance or required shipping and transport capacities. The altered tour characteristics might lead to a different mode choice decision compared to a direct commuting tour.

To determine the modal split of the different tour types, *car as driver* is the dominant mode used (64% of all tours). *Public transportation* is used for 14% of all tours, followed by *bicycle* (12%) and *walking* (6%). *Car as passenger* is used for 4% of all commuting tours only. This modal split reflects mainly the modal split of direct commuting tours as they represent the majority of the tours done. Investigating tours including additional activities only, we identify a mode shift towards a higher level of car usage. The inclusion of a shopping activity leads to 70% usage of cars and the integration of a service activity even to 81%. The increase in car usage goes along with decreasing splits for the modes *bicycle* and *walk*. These findings suggests that there might be a relationship between mode usage and characteristics of the integrated activity, e.g. persons who do service tours might rather choose the car since it is particular suitable to carry children fast, safe and comfortable.

Descriptive Analysis of Activity- and Mode-based Commuting Behavior Types

In the following, we change our focus from tour level to the individual level given the context of whole week. FIGURE 1 shows the share of persons in each activity based commuting behavior group.

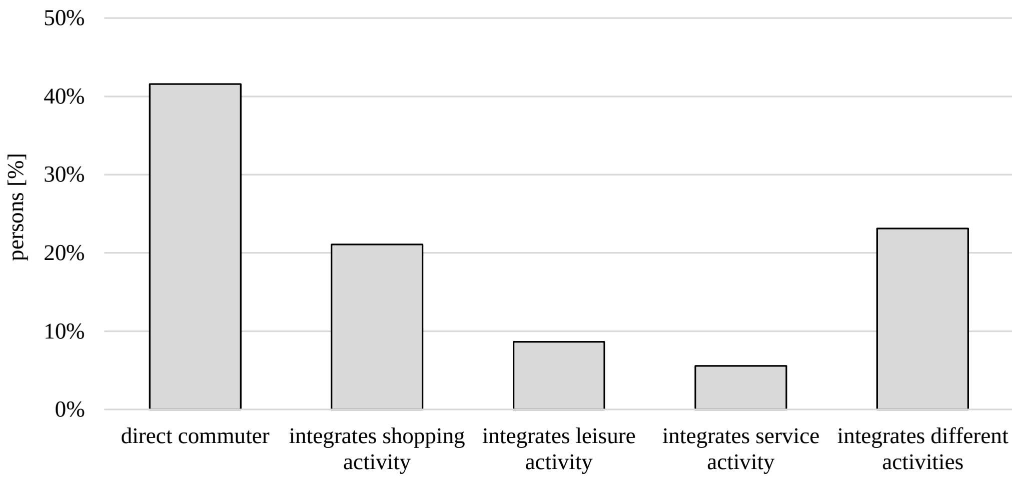

FIGURE 1 Proportions of the different activity based commuting behavior types.

Only 42% of all persons are direct commuters, i.e. they did not integrate another activity within any commuting tour. Whereas the findings in the previous section show that three quarter of the commuting tours are direct tours, the analyses on the individual level emphasize indeed that the integration of additional activities is relevant: 58% of the commuters execute at least one tour with an additional activity during the survey week. 23% of all persons integrate even several different activity types in their commuting tours.

The frequency of the integration of additional activities depends on the activity type. Persons who include shopping activities, integrate them on 38% of their tours (ratio of tours including shopping / all tours); whereas persons who include service activities, integrate them on 50% of their tours on average (ratio of tours including service / all tours).

We also examine commuting mode choice in the context of the week. As introduced in the methodology section we determined a main mode used for every person. FIGURE 2 shows the modal split of the main mode used for commuting per person and the respective multimodal behavior shares (hatched areas). As expected *car as driver* is the dominant mode. 65% of all persons use this mode as their main commuting mode, followed by the use of *public transportation* and *bicycle* (both 13%). Our analysis indicates a causal relation between the main mode used and the probability of multimodal commuting behavior. The relative share of multimodal commuters is significantly smaller among the group of car commuters (18% of all car commuters) than the multimodal shares in the group of walking (47%), bicycle (48%) or car-passenger commuters (68%). These shares of multimodal behavior clarify and expose some characteristics of the different modes. The car is known as a universal mode of transportation which can be used for various activities and offers a great flexibility. In contrast to that, being a car-passenger commuter reduces a lot of that flexibility and does hardly allow for the integration of additional activities. The same holds true for bicycle and walking commuters.

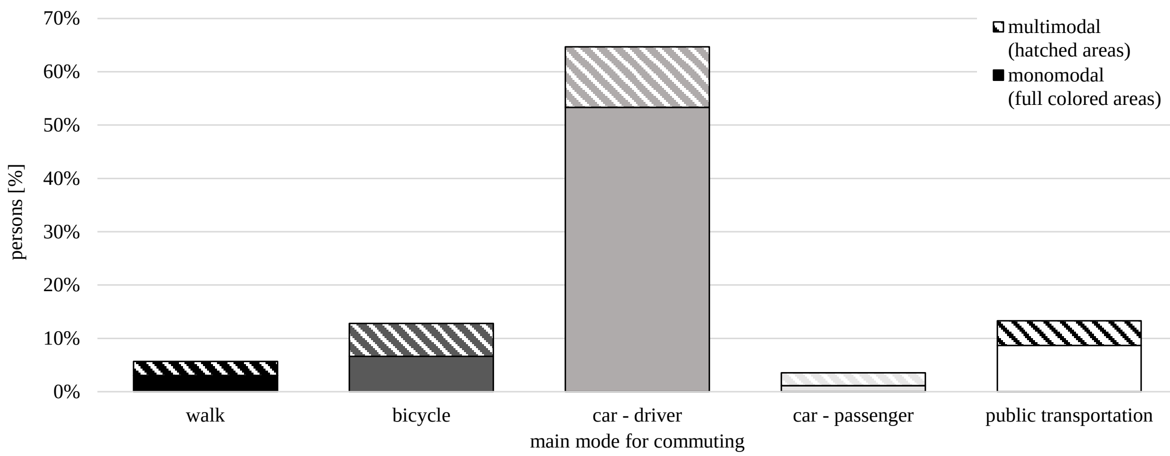

FIGURE 2 Proportions of the different mode based commuting behavior types.

Looking at multimodal commuters only, FIGURE 3 shows which modes multimodal commuters use besides their main mode (main mode is shown on the x-axis). The y-axis shows the share of persons who use other modes for commuting at least once in the survey period.

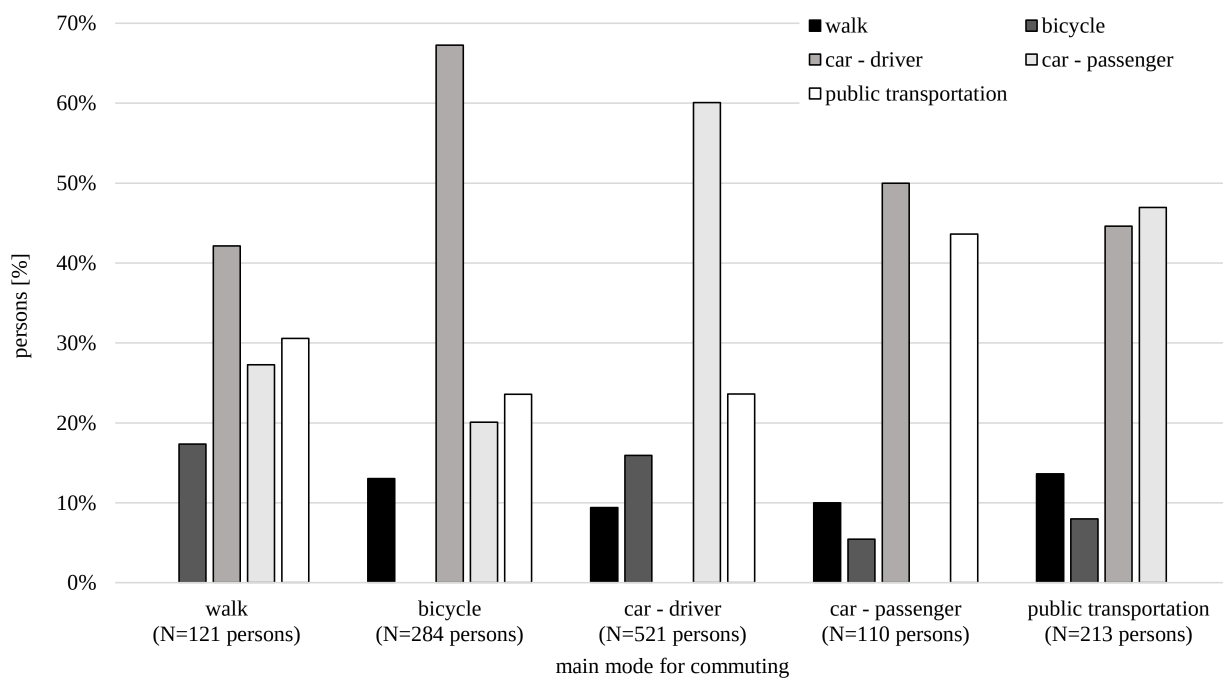

FIGURE 3 Multimodal commuters – shares of persons using other modes besides main mode.

This analysis emphasizes that *car as driver* is the dominant alternative mode among multimodal commuters. Given the three named examples (commuting as *car-passenger*, by *bicycle* or *walking*) car usage always dominates the other modes. Another interesting aspect is the high *public transportation* shares for multimodal car passengers, and, vice versa the high *car passenger* shares for multimodal public transportation commuters. This shows a relation between the usage of *public transportation* and *car as passenger*, indicating that these persons might not have a car at their disposal.

A combined descriptive analysis of the two perspectives of activity integration and mode usage might give additional insights in commuting behavior.

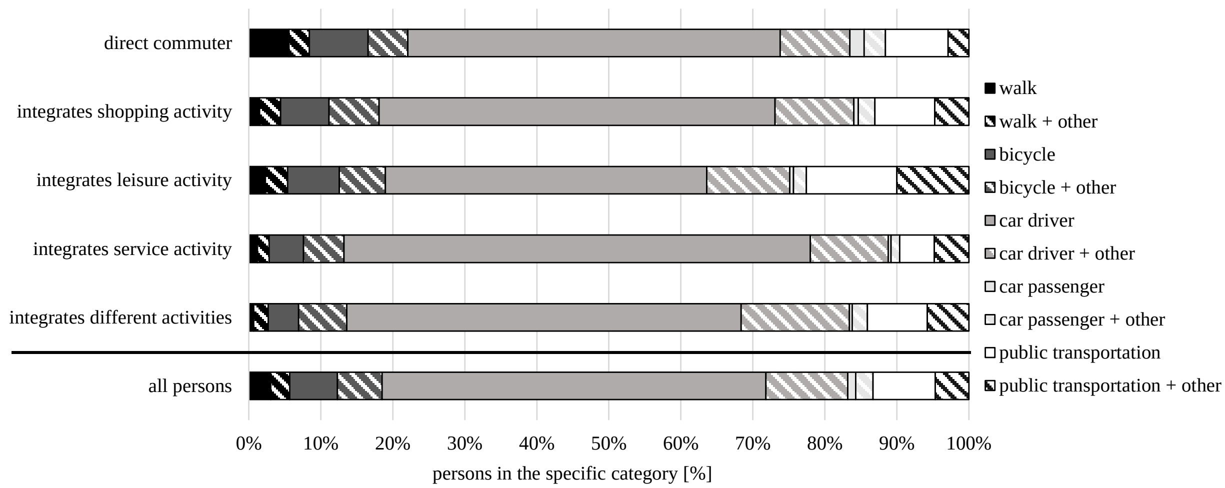

FIGURE 4 Combination of activity and mode based commuting behavior type.

FIGURE 4 shows the combination of activity and mode based commuting behavior type. The share of monomodal car commuters is highest in the group of persons who integrate service activities. Persons integrating leisure activities show a high usage of *public transportation*, both in the group of monomodal and multimodal commuters; as well the share of monomodal car users is among the smallest compared to other activity based commuting types. This reveals the question whether these activity based commuting types adapt their mode choice only because of the integrated activities. To further investigate these questions we combined individual level and tour level perspectives to show the tour-based modal splits, grouped by activity based commuting types (TABLE 2).

TABLE 2 Tour-Based Modal Split for Activity Based Commuting Behavior Groups

mode	direct tour	tour including shopping activity	tour including leisure activity	tour including service activity
Direct commuters				
walk	9%	na	na	na
bicycle	14%	na	na	na
car - driver	61%	na	na	na
car - passenger	5%	na	na	na
public transportation	12%	na	na	na
	N=8,411 tours	na	na	na
Persons who integrate shopping activities				
walk	5%	3%	na	na
bicycle	14%	11%	na	na
car - driver	65%	70%	na	na
car - passenger	3%	3%	na	na
public transportation	14%	14%	na	na
	N=3,048 tours	N=1,510 tours	na	na
Persons who integrate leisure activities				
walk	7%	na	5%	na
bicycle	13%	na	12%	na
car - driver	56%	na	55%	na
car - passenger	4%	na	4%	na
public transportation	21%	na	23%	na
	N=1,283 tours	na	N=570 tours	na
Persons who integrate service activities				
walk	3%	na	na	2%
bicycle	11%	na	na	7%
car - driver	72%	na	na	81%
car - passenger	4%	na	na	1%
public transportation	10%	na	na	8%
	N=561 tours	na	na	N=547 tours
Persons who integrate different activities				
walk	4%	1%	2%	1%
bicycle	12%	9%	7%	6%
car - driver	66%	70%	65%	82%
car - passenger	3%	2%	3%	2%
public transportation	15%	17%	23%	10%
	N=1,932 tours	N=1,757 tours	N=1,233 tours	N=1,079 tours

na = not applicable

Investigating tours of persons who integrate service activities we see a high usage of cars mainly on service tours. Nevertheless, the usage on direct tours is still above average (64%). Examining persons who integrate leisure activities, car usage is below average on both tour types. Hence we assume an influence of the integration of additional activities not only on the tour types that include the activity but also on mode choice behavior in general.

Logistic Regression – Estimation Results

Our descriptive analysis shows that 27% of all commuters have a multimodal behavior and use more than one commuting mode within the survey period. This might be caused by the integration of additional activities in the commuting tours; 58% of all persons integrate at least one additional activity in their commuting tours. To explain further which factors do influence the mode choice and mode variation we expose the multinomial logistic regression results for the estimation of the mode based commuting behavior type. The following table shows the parameters for the utility functions. All parameters are significant on the 0.01 level.

TABLE 3 Logit Parameter Estimates

Parameter Estimates	**walk**	**walk + other**	**bicycle**	**bicycle + other**	**car driver**	**car driver + other**	**car passenger**	**car passenger + other**	**public transportation**	**public transportation + other**
Intercept	3.384	ns	1.940	1.215	Ref	-0.763	-1.592	-1.082	-1.984	-2.211
socio-demographic attributes										
Household with one adult, working, no kids	ns	-0.704	-0.826	-0.941	Ref	-0.525	ns	-1.343	-0.793	-0.795
Household with at least 3 adults and at least 2 working persons, no kids	1.578	ns	ns	0.721	Ref	ns	1.744	ns	1.082	1.543
male	ns	-0.662	ns	ns	Ref	ns	ns	-0.905	-0.572	-0.707
commuting tour characteristics										
ratio tours including shopping / all tours	-3.668	ns	-0.913	ns	Ref	ns	ns	ns	-1.149	-1.212
ratio tours including service / all tours	ns	-3.716	-0.986	ns	Ref	ns	ns	-2.988	-2.040	-1.383
direct distance work - home	-2.059	-0.119	-0.253	-0.154	Ref	ns	ns	ns	0.010	ns
facilities										
number of cars in household	-1.383	-1.509	-1.603	-1.462	Ref	-0.411	-1.195	-1.096	-1.696	-1.473
transit pass ownership	ns	1.789	0.817	1.248	Ref	1.261	ns	2.694	5.424	5.336
transportation system based factors										
parking pressure at work place is high	1.131	ns	0.629	ns	Ref	ns	ns	ns	0.875	0.808
workplace located in city center	ns	ns	0.522	0.604	Ref	ns	ns	ns	1.042	0.779

NOTE: Results of multinomial logistic regression; all parameter estimates significant at the .01 level.
Number of observations = 4,510; McFadden's Pseudo R-squared = 0.301; Ref = Reference; ns = not significant

Socio-demographic attributes

Our regression model indicates that commuting mode choice depends on socio-demographic characteristics of commuters. We estimate three parameters for the multinomial logit model in this category. All variables are binary coded. Single-person households are mainly monomodal car commuters. All other options result in a decreased utility value. Their best alternative is *car as driver* in combination with other modes (multimodal behavior). Single-person households are least likely multimodal car-passenger commuters since carpooling often necessitate family members.

Households with at least three adults and at least two working persons show a quite different behavior. They rather use other modes than *car as driver* like *car as passenger* due to several possibilities resulting of the household circumstances, e.g. probably not all working household members have their own car. The logit parameters reveal that the higher variety is not only an option but also a need due to the non-availability of a car for commuting.

Third, our investigation indicates that commuting mode variation is affected by gender: men prefer *car as driver* over other modes. This finding contradicts other mode usage analyses in industrialized countries: they found that men are more likely to commute by non-motorized transportation modes (*5; 11*). Men are also less multimodal (compared to the base case of car usage); three multimodal options result in a negative utility value.

Other socio-demographic variables such as age, education level and household income have been tested but occurred not to be significant in our logistic regression model.

Commuting tour characteristics

Our model indicates that characteristics of the commuting tours also impact the variation of commuting mode choice. Three tour characteristics were found to be significant: The relative amount of tour types including shopping activities, the relative amount of tour types including service activities and distance from home to work location, measured in kilometers. As we assumed the integration of additional activities into tours has a significant impact on the mode choice decision. The two ratio variables confirm that hypothesis. An increasing ratio indicates that more tours have additional activities what results in negative utility values for all other options than the reference category. Concerning the integration of shopping, especially the mode *walk* has a high negative value. Shopping often requires shipping capacities that are rather available in a car. The service ratio variable reveals that *car as passenger* and *public transportation* are unlikely to work together with additional service activities since these modes effect a dependence from schedules or other persons. Overall the high utility values show that these variables are valuable additional parameters for the estimation of the mode based commuting behavior type. Furthermore, the distance variable estimates reveal that commuting *walking* and by *bicycle* is less preferred with increasing distance. This is in line with other studies on commuting mode choice (*5; 13; 11*) and a common aspect of mode choice in general. With an increasing distance *public transportation* is slightly favorable compared to the base category. However, distance from home to work impacts multimodal bicycle and walking commuters less than monomodal walking and bicycle commuters. This finding might be explained by the matter of fact that most of the multimodal bicycle and walking commuters use *car as driver* from time to time.

Further commuting tour characteristics such as the relative amount of tours including leisure activities or travel time have been tested but occurred not to be significant in our model. Cost data for each trip (transit, parking or fuel costs) were not available in the dataset and thus could not be used for our logistic regression model.

Facilities

Commuting mode choice also depends on the facilities commuters have available. Two variables were found to have a significant impact: the number of cars in the household (discrete variable) and transit pass ownership (binary coded). Similar to other studies (*22; 10*), we figure out that a rising number of cars in the household reduces the utility of using other commuting modes in general. Furthermore, the number of cars in the household reduces the utility of monomodal commuting types in most cases more than the utility of the corresponding multimodal commuting type. This confirms the findings of the descriptive analysis on the usage of cars as an alternative commuting mode (see FIGURE 3). If more cars are available, persons will tend to use them as alternatives to their main commuting mode. As expected, transit pass availability has a positive impact on the usage of *public transportation*. Furthermore, transit pass possession raises the probability for multimodal commuting. Multimodal commuters might own a transit pass in order to commute by *public transportation* in situations where their main mode is less favorable, e.g. bicycle and walking commuters might use *public transportation* in case of bad weather conditions.

Transportation system based factors

Commuting mode choice might also depend on the characteristics of the transportation system. Parking pressure at work place and a work place in the city center influences the commuting mode choice significantly. Both variables are binary coded. The parking pressure estimates show positive utility values for the monomodal commuting modes *walk*, *bicycle* and *public transportation*. This might be caused by the fact that these modes do not need a parking lot. With the exception of multimodal public transportation commuters, parking pressure has no significant impact on multimodal commuting groups. A reason for the non-significance compared to the reference category (*car as driver*) might be that multimodal commuters often use cars as an alternative mode (see FIGURE 3). This option is not favorable since parking pressure is high. Subsequently this fact might trigger monomodal uses in addition.

The location of the working place in the city center has a positive influence on *bicycle* and *public transportation*. This is reasonable since bikeways quality and public transportation connections are often better in city centers what offers alternatives to the car usage of a better quality.

CONCLUSION

To explain mode choice variations in general, the investigation of commuting-related travel behavior is especially important since a huge part of everyday travel is work-related. We investigated the stability and flexibility in commuting behavior, especially in mode choice and mode variation. 27% of all commuters use more than one commuting mode during the survey period (one week). Since one-day travel surveys might not be sufficient to expose the variations in commuting mode choice, longer periods like a whole week are necessary.

We furthermore investigated reasons that cause a variation (multimodal behavior) in commuting mode choice by examining mode choice patterns. Our multinomial regression model shows that various factors (socio-demographic attributes, commuting tour characteristics, the availability of cars and transit passes, transportation system based factors) support mode choice and mode variation and thus a multimodal behavior. An additional layer of information that was not yet examined in other studies is the complexity of commuting tours, i.e. whether commuters integrate additional activities on their ways from home to work and back. 58% of all commuters integrate at least one additional activity within the survey period; these aspects turned out to be significant in the multinomial regression model.

For transportation planning, especially for mobility management concepts, the following implications can be derived from our findings: Employers should think about a way to offer various options for the usage of different modes in order to reflect the flexibility of the employees. Our results may help to quantify the necessary infrastructure supply for different modes at work place. It is important to provide car parking lots but also parking space for bicycles. Car parking lot supply may be both personal and flexible while some commuters do not vary their mode usage but other employees commute multimodal and can share a pool of common parking lots. Additionally, our results can help to steer mode choice. Since transit passes have a high significant influence on the use of *public transportation*, a promotion of these passes by employers can be an additional aspect of the operational mobility management.

Our presented analyses are a valuable and necessary basis for further research. As shown, the integration of activities in commuting tours has a certain influence on mode choice. Additional research identifying the specific situations and circumstances for changing the main mode can be an additional benefit. For planning purposes, answering these questions is interesting since multimodal options can be promoted and solutions can be provided for these situations more specifically. Further, more detailed investigations on the switchover from monomodal to multimodal behavior in the mode groups (e.g. changing from *public transportation* to multimodal *public transportation* commuter type) can also be conducted using our methodology.

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