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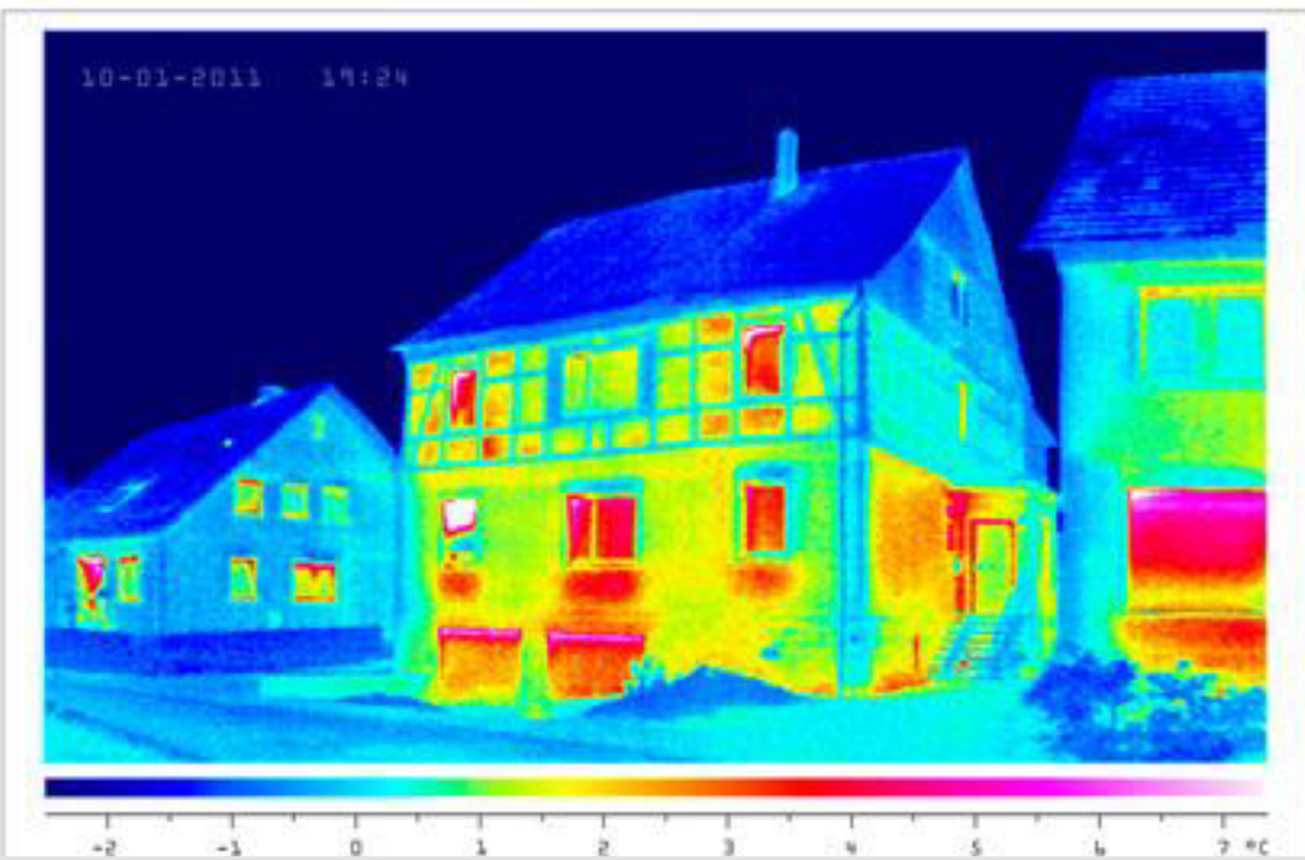

Behavior-oriented Modeling of Electric Vehicle Load Profiles: A Stochastic Simulation Model Considering Different Household Characteristics, Charging Decisions and Locations

Alexander Harbrecht, Russell McKenna*, David Fischer, Wolf Fichtner

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This paper presents a stochastic bottom-up model to assess electric vehicles' (EV) impact on load profiles at different parking locations as well as their load management potential assuming different charging strategies. The central innovation lies in the consideration of socio-economic, technical and spatial factors, all of which influence charging behavior and location. Based on a detailed statistical analysis of a large dataset on German mobility, the most statistically significant influencing factors on residential charging behavior could be identified. Whilst household type and economic status are the most important factors for the number of cars per household, the driver's occupation has the strongest influence on the first departure time and parking time whilst at work. An inhomogeneous Markov-chain is used to sample a sequence of destinations of each car trip, depending (amongst other factors) on the occupation of the driver, the weekday and the time of the day. Probability distributions for the driven kilometres, driving durations and parking durations are used to derive times and electricity demand. The probability distributions are retrieved from a national mobility dataset of 70,000 car trips and filtered for a set of socio-economic and demographic factors. Individual charging behaviour is included in the model using a logistic function accounting for the sensitivity of the driver towards (low) battery SOC. The presented model is validated with this mobility dataset and shown to have a deviation in key household mobility characteristics of just a few percentage points. The model is then employed to analyse the impact of uncontrolled charging of BEV on the residential load profile. It is found that the absolute load peaks will increase by up to factor 8.5 depending on the loading infrastructure, the load in high load hours will increase by approx. a factor of 3 and annual electricity demand will approximately double.

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List of Abbreviations

# ...	Number of ...
AC	Alternating current
ANOVA	Analysis of Variance
apcc	Active power charging curve
BEV	Battery electric vehicle
BMVI	Bundesministerium für Verkehr und digitale Infrastruktur (Federal Ministry of Transportation and Digital Infrastructure)
CATI	Computer assisted telephone interview
CAWI	Computer assisted web interview
CCCV	Constant current constant voltage
CDF	Cumulative distribution function
CLT	Central limit theorem
CI	Confidence interval
cf.	Latin: confer (compare)
SOC	State of charge
DC	Direct current
df	Degrees of freedom
DLR	German: Deutsches Zentrum für Luft und Raumfahrt (German Aerospace Center)
EV	Electric vehicle
EVSE	Electric vehicle supply equipment (charging station)
emobility	Electric mobility
FDR	False discovery rate
FWER	Family-wise error rate (Type I error inflation, multiple comparison problem)
GLM	Generalized Linear Model
ICEV	Internal combustion engine vehicle
KiD	German: *Kraftfahrzeugverkehr in Deutschland 2010* (Motor Traffic in Germany in 2010)
KS	Kolmogorov–Smirnov test
LR	Linear Regression
MiD	German: *Mobilität in Deutschland 2008* (Mobility in Germany in 2008)
MOP	German: *Deutsches Mobilitätspanel* (German Mobility Panel)
PAPI	Paper and pencil interview
PEV	Plug-in electric vehicle
PDF	Probability density function
PHEV	Plug-in hybrid electric vehicle
PUF	Public Use File (from MiD data)
rbW	German: Regelmäßige berufliche Wege (regular job-related trips)
UBIS	User-battery-interaction style
V2G	Vehicle-to-grid
X	Independent variable/explanatory variable/factor
Y	Dependent variable/variable being explained/response variable
ZF	German: Zusatzfile (Additional File from MiD data)

1 Introduction

In Germany approximately 33% of end energy consumption in the household sector is used for fueling cars (BDEW, 2010). A change of energy carrier in the transportation sector from fossil fuels to electricity can help to reduce the CO_2 emissions but will impact residential electricity consumption (Richardson, 2013). In January 2016 25,502 electric vehicles have been registered in Germany (Kraftfahrtbundesamt, 2016), by 2030 the German Federal Government plans the number to be around 6,000,000 (Bundesregierung, 2011).

Electric vehicle charging will put new challenges on distribution grid planning and operation (Veldman et al., 2013). On the other hand using electric vehicles' flexible storage capacities could proof a potential solution to integrate high shares of renewable electricity into the power system (Lund et al., 2015; Babrowski et al., 2014; Kempton and Letendre, 1997). To fully evaluate the potential benefits and risks of a large scale deployment of electric vehicles in electric distribution grids, accurate models for load profile generation regarding electric vehicle charging are needed.

Residential load profiles resulting from electric vehicle charging have been studied intensively in recent years based on simulations using empirical driving data from mobility surveys most of the time with a focus on home-charging (Munkhammar et al., 2015; Garcia-Villalobos et al., 2015; Babrowski et al., 2014; Grahn et al., 2014; Grahn et al., 2013; Su et al., 2012). More recent approaches focus on empirical charging data of fleets (Schäuble et al., 2017*b*; Wieland et al., 2015). However, none of these approaches allow for a detailed examination of driving behavior differentiated by socio-economic, sociodemographic and temporal aspects. Moreover, most mobility survey approaches generally assume *charging upon arrival for every parking event*, neglecting possible behavioral preferences regarding the charging decision, which have a major influence on the electric vehicle's charge level at which people typically recharge (Franke and Krems, 2013; Schäuble et al., 2017*b*). This results in synthetic load profiles that may be contradictory to empirical findings on the average number of vehicle charging events per day, the average vehicle's charged energy per day and location-dependent charging preferences from field trials (Schäuble et al., 2017*b*; Morrissey et al., 2016; Azadfar et al., 2015; Franke and Krems, 2013; Jabeen et al., 2013).

Focusing on these behavioral aspects of electric vehicle charging, the following research questions are proposed for the present work:

I *How can driving behavior of private households in Germany be differentiated by socio-economic, sociodemographic and temporal characteristics?*

II *How can different charging locations and decisions be considered in synthetic load profile simulation models?*

III *What are the characteristics of simulated electric vehicle charging load profiles with location-dependent charging decisions and sociodemographically differentiated driving behavior compared to models using empirical electric vehicle charging data?*

Chapter 2 firstly presents the fundamental theory of mobility and transportation as well as information on different types of electric vehicles followed by empirical evidence of electric vehicles' charging regarding impacts on the power system. Next, an overview of different influential domains related to electric vehicle charging is given. Following an *inductive* research approach, findings with respect to the behavioral domain presented before are used to statistically test and evaluate possible influencing factors regarding internal combustion engine vehicles' (ICEV) driving behavior in Germany (cf. Chapter 3). Results lead to a possible socioeconomic and sociodemographic differentiation of households' driving behavior answering research question I.
Based on the assumption that driving behavior is independent from the type of drive, these insights, together with information on other influential domains illustrated before, are then used to model battery electric vehicle (BEV) charging on a system level, making use of a simulation approach (cf. Chapter 4). Thereby it is shown how connection and charging decisions of EV users can be incorporated into the model answering research question II.
Finally, section 4.3 compares simulated electric vehicle load profiles with indicators from different field trials and synthetic load profiles from a most recently developed simulation model using empirical charging data providing an answer to research question III. Subsequently, a final conclusion as well as an outlook on methodological improvements and exploratory analysis are given.

2 Fundamentals

2.1 Mobility and transportation

First of all, the terms *mobility* and *transportation* have to be defined and differentiated as they are often used synonymously and are not mutually exclusive. The word mobility comes from the Latin word ‘mobilis’ which means movable. To satisfy ones needs, people or organizations need access to other people or organizations, services and goods.

Mobility describes the possibility or ability to achieve these aims by temporal and spatial change of location, e.g. to enable and combine activities like living, working or relaxation. Therefore it can be said that mobility is a precondition for individual development and the performance of a society, in which every single one and all sociodemographic groups have demands on mobility. These mobility needs can be satisfied depending on the technical, economical and social development of a region and the social status of every individual. One could state that mobility reflects the dynamic and flexibility of a society.
In contrast, the term transportation signifies the realized mobility and describes the aggregated change of location of people, goods or information to satisfy the mobility needs. The amount of transport is dependent on the needs which can be satisfied by means of transport. To record and analyze temporal-spatial movement in a scientific context regarding traffic, movement of persons and goods is measured in volume of transport and transport capacity. There is a strong link between mobility and transport since the behavior of persons regarding their realized and possible changes of place is a central factor for the volume of transport and transport capacity. However, a high degree of mobility does not mean a high level of transport, as transport is not generated by potential mobility only. Therefore the aim of a flexible and sustainable transport policy should be a maximum amount of mobility with a minimum of transport (Bertram and Bongard, 2013).

Passenger transportation (i.e. the transport resulting from the mobility needs of individual persons) can be subdivided into *private transportation* and *public transportation*. The difference between private and public transportation by transport means and distance is illustrated in Table 1. Private transportation can be distinguished between *motorized private transportation* (e.g. cars or motorcycles) and *non-motorized private transportation* (e.g. bicycles or on foot). Public transportation can be subdivided into *local passenger transportation* (e.g. trams or taxis) and *long-distance passenger transportation* (e.g. trains or planes). Regarding private transportation, means of transport are used with free decision of route and time (except for having travel commitments to passengers) whereas people using means of transport of the public transportation sector are bound to time and place of the departure.

Table 1: Different forms of passenger transportation by transport means and distance based on (Bertram and Bongard, 2013)

Passenger transportation			
Private transportation		**Public transportation**	
Non-motorised private transport (rather local)	Motorised private transport (rather non-local)	Local passenger transport	Long-distance passenger transport
e.g. on foot, bicycle, inline skates	e.g. car, moped, motorcycle, car sharing, caravan	e.g. tram, taxi, suburban train, regular bus	e.g. train, tour bus, plane

Another way to subdivide passenger transportation is to differentiate transportation by its purpose. For example, mobility needs can be either motivated *personally* or *commercially*. Therefore it is important to keep in mind that passenger transportation has an intersection with *commercial transportation*, that relates to the aggregated change of location of goods, persons and messages which result from the production of goods or services, the supply of organizations and waste disposal. For example, business trips or other regular job-related trips of individual persons therefore relate both to the passenger transportation and commercial transportation domain.

2.2 Electric vehicles (EV)

Particularly relevant with regard to the field of electric mobility (emobility) is the sector of *motorized private transport*. There are differing opinions regarding the definition of emobility, for example that besides vehicles that are purely battery-powered, all forms of hybrid drives and fuel cell vehicles are included in emobility regarding passenger cars. According to Wietschel (2010), emobility concerning motorized private transport is related to vehicles that are powered by electric motors and that have a relevant amount of energy stored in the form of electricity in batteries or chemically bound in hydrogen. Such vehicles are hybrid vehicles, plug-in hybrid vehicles, purely electrically powered vehicles and hydrogen powered vehicles with fuel cells. The German Federal Government defines that electric vehicles only concern vehicles obtaining most of the required energy from the grid and that are powered by electric motors, such as purely electrically powered vehicles, electric vehicles with range extenders and plug-in hybrid-vehicles (Bundesregierung, 2009, p. 7).

For the present work, purely battery-powered vehicles are of most interest, since they may have the largest impact on the power system, but also provides the the highest CO2 reduction potential when deployed in the mass market. In the following, a classification of the most important drive concepts of electric and hybrid technology will prove further justification for this claim (cf. Table 2 for a general overview).

Mild hybrid and full hybrid

Vehicles with combustion engine, that recuperate energy during braking by an electric motor are called mild hybrids. Energy regained trough recuperation is saved in a hybrid battery and can be released to support the combustion engine when accelerating (Buchert et al., 2011). A further development regarding the electrification of vehicles is the full hybrid. It is characterized by a more powerful electric motor and a higher capacity of its battery, which allows for purely electrically powered traveling of short distances (Buchert et al., 2011). In contrast to the mild hybrid, energy for charging the battery is also generated by the combustion engine (Spath et al., 2010).

Table 2: Different types of electric Vehicles based on (Bundesregierung, 2009)

Designation	Vehicle type	Grid usage in %	Electric vehicle*
Battery electric vehicle (BEV)	Electric vehicle	100%	Yes
Range extended electric vehicle (REEV/EREV)	Electric vehicle with range extender	ocassionally, depending on battery range and usage	Yes
Plug-in hybrid (PHEV)	Hybrid electric vehicle with grid connection	ocassionally, depending on battery range and usage	Yes
Mild or full hybrid (MHEV/FHEV)	Hybrid electric vehicle without grid connection	no grid connection	No
Fuel cell hybrid (FCEV)	Electric vehicle with fuel cell	no grid connection	No

*Defined as an EV throughout this work

Plug-in hybrid

Plug-in hybrids can be considered as further developments of full hybrids and bridging technology on the way to full-electric mobility. Plug-in hybrids are fitted with still more powerful electric motors and accumulators than full hybrids to travel longer distances in fully electrically powered mode. A smaller combustion engine is used in situations that require more power than the electro motor is able to provide (e.g. fast driving) or in case of a discharged battery. Doing so allows for electrically powered ranges up to 30 km. Battery charging can be undertaken by plugging the car into a standard household socket or connecting it with a public charging station. While driving, the battery can be recharged trough recuperation during braking (Bertram and Bongard, 2013).

Electric vehicles with a range extender

In addition to a very strong electric motor, electric vehicles with range extenders are fitted with a small combustion engine, that in contrast to full and plug-in hybrids, is used to stabilize the charge state of the battery. If the battery level drops below a certain threshold, the battery and all electrical auxiliary devices are powered by a small internal combustion engine together with a generator. An electric motor with 50 kW or more is used for driving. Electric vehicles with range extenders enable driving long distances that previously were only done by conventionally motorized vehicles (Buchert et al., 2011).

Battery electric vehicles (BEV)

Whereas all described drive concepts were based on a combination of an electric motor and a combustion engine, battery electric vehicles are powered by electric motors exclusively. All required energy is obtained from the grid, entailing a high potential for CO2 reduction by using renewable energies (Bundesregierung, 2009). BEVs are fitted with powerful electric motors with 50 kW or more and batteries with 15 kWh or more depending on the required range and use. Still, the limited capacity of accumulators results in a restricted range of purely battery-powered electric vehicles in comparison to vehicles powered by combustion engines. If the charging level is low, BEVs usually have to be charged for several hours, particularly when using the one-phase voltage of a standard socket (Buchert et al., 2011).

The following literature review focuses on three areas: first, the general context of the work, related to integration of EV into the electric power system, second, the empirical work done in the field of influencing factors on EV charging and finally, the current state of research of existing EV charging models demonstrating the contribution of this work. This threefold examination provides insights into the current state of all three fields.

2.3 Impacts of EV charging on the power system

EV mass market roll-out for private households in Germany would shift up to 33% of current end energy consumption in the household sector ($1059 \cdot 10^9$ kWh) from fossil energy carriers used for fueling cars to the power system (BDEW, 2010). Besides electric vehicle charging affects the performance, efficiency, and required capacity of the electric grid, especially if vehicle charging is unconstrained (Richardson, 2013). Under a simple charging strategy peak loads will increase, requiring extra investment in generation and transmission (Hadley, 2006). When only considering the last arrival time per day, peaks were found to max out in the evening or night between hour 18:00 and 01:00 dependent on the charging power and possible countermeasure policies (Darabi and Ferdowsi, 2011). In order to minimize the impact of EV charging on the distribution grid, demand response measures with customer choice were found to be able to mitigate distribution grid reenforcement while keeping consumer comfort levels within the boundaries of a predefined comfort zone (Shao et al., 2012). An optimized simulation approach could demonstrate that certain demand response strategies can successfully optimize charging schedules with benefits both for the EV owner in terms of charging cost minimization and the utility company in terms of peak load reduction and minimization of peak load hours (Zhao et al., 2013). Moreover, optimized charging schedules for full-time employees were found to double the share of charged energy consumed from renewable energy sources while load peaks and the amount of conventional generation as backup can be decreased with coordinated charging (Gottwalt et al., 2013). In contrast a 2030 case study for California and Germany revealed that uncontrolled charging and corresponding demand side measures such as static time-of-use tariffs do not significantly improve integration of renewable energies but it was found that vehicle-to-grid (V2G) concepts play an important role in reducing residual load fluctuation by renewable energies (Dallinger et al., 2013). Further analysis also demonstrated that with increased information and communication technology use, flexible consumption units such as electric vehicles can be integrated in ancillary markets without violating the limitations (Biegel et al., 2014). Further modeling using a multi-agent-approach with respect to market-based coordination mechanisms on an upper (DSO) and lower (EV owner or fleet operator) level of the system suggested that EV user's price sensitivity can be individually considered (Hu et al., 2015). More recent studies focus on detailed analysis of different control and charging strategies of electric vehicle fleets (Hu et al., 2016; Braam et al., 2016; Ramos Muñoz et al., 2016; Flath and Gottwalt, 2016), and a further investigation of flexibility and V2G-concepts (Gottwalt et al., 2016; Tarroja et al., 2016).

2.4 Influencing factors on EV charging

Influencing factors on electric vehicle charging are crucial to a systemic understanding of impacts of EV charging of private households on the power system. In general, the influence can be subdivided into three major domains: first, the behavioral and economic domain, second, the spatial domain and third, the technical domain. However, all three domains are not mutually exclusive so that there are aspects that relate to more than one category. Figure 1 tries to provide a holistic overview without claiming to be collectively exhaustive.

Behavioral & economic domain

First of all, driving behavior can considerably influence electric vehicle charging as it influences the amount of energy consumed while driving as well as the time and frequency of recharging intentions. Typical variables to characterize driving behavior are the number of trips driven per day, the vehicle use frequency (e.g. daily, weekly, monthly), departure and arrival places, the driven distance as well as departure and arrival times (or driving and parking times respectively) per trip (Follmer et al., 2010*a*; Wermuth et al., 2012; Weiss et al., 2014). All variables may be influenced by household, person and trip attributes as well as temporal aspects such as the weekday of the vehicle use.

Besides driving behavior, connection decisions play an important role with respect to the time and frequency of taking charging decisions. An important finding from a field trial in Germany suggests that the initial battery's SOC upon recharging in combination with other factors such as 'comfortable range' may explain a large proportion of electric vehicle recharging (Franke and Krems, 2013). Other field trials show preferences for different charging locations and reveal preferences for fast-charging, i.e. charging at high power levels consequently reducing the required time to charge a specific energy amount (Jabeen et al., 2013; Azadfar et al., 2015; Morrissey et al., 2016).
Moreover, the existence and type of control over the charging process can be an important aspect affecting the time, frequency, charged energy and load profile of electric vehicle

charging. If there is no exertion of influence on the charging process at all so that it just results from the driving behavior and the connection decision of the electric vehicle user, one speaks of *uncontrolled charging*. However, several ways to control the charging process are conceivable: the control can emanate from an operator or the EV user himself. The former could aim at maximizing revenues from ancillary services or minimizing load peaks. The latter might focus on a minimization of charging costs or CO2 emissions. From that, note that an optimum for an individual EV user may not necessarily equal a system optimum.
There are several behavioral drivers that also relate to the spatial domain such as driving behavior influenced by the household's place of residence (e.g. agglomerations such as 'rural', 'urban', 'city'). Even though Babrowski et al. (2014) state that neither "national nor regional differences are as significant as the possibility to charge at work" with respect to Germany, the analysis of the household's place of residence is still open to a quantitative assessment. Furthermore, connection and and charging decisions influenced by, e.g. security considerations with respect to the charging locations and its surroundings as well as the accessibility of charging stations in terms of time and distance to the closest idle charging station, can impact electric vehicle charging.

Spatial domain

Form a systemic point of view, the expected market penetration of electric vehicles is an important spatial aspect since a majority of EVs will certainly be located, drive and be willing to recharge in rather concentrated in urban or city areas where distribution grids, e.g. in Germany, are already confronted with challenges due to high shares of intermittent and decentralized electricity production. Analogously, the market penetration of charging stations is not expected to be uniformly distributed in terms of spatial expansion. The German National Electric Mobility Platform (NPE) identified three main locations for charging stations with respect to the expected charging powers: first, private locations such as garages of single family houses or parking lots/basement garages of multi-family houses as well as company car parks or public charging stations for on-street parking with relatively low charging power, second, semi-public charging stations, e.g. at supermarkets, shopping malls or public car parks with relatively high charging power and fast-charging stations, e.g. along highways (Nationale Plattform Elektromobilität, 2015).

Technical factors

EV
- energy consumption in kWh/100km, dependent on e.g. velocity, rim size, vehicle weight, aerodynamics, heating/cooling of passenger cell
- v_{max} in km/h
- total battery size in kWh
- usable battery share in %
- self-discharging rate in %
- nominal charging power of internal charger $P^{EV}_{nominal}$ in kW and its efficiency

Charging station
- nominal charging power of external charger $P^{EVSE}_{nominal}$ in kW and its efficiency

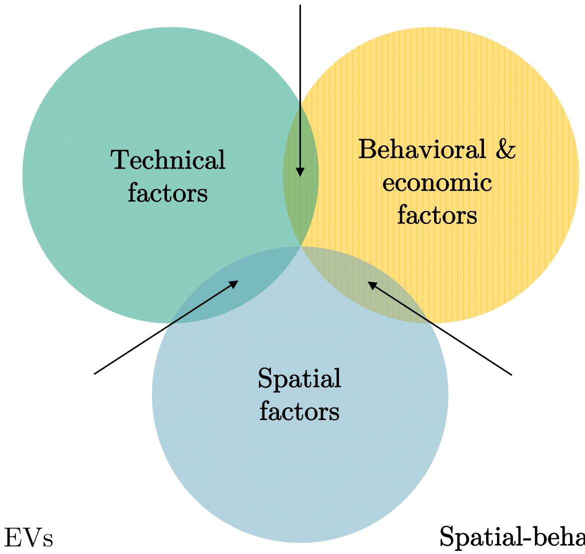
Technical-behavioral factors

Connection & charging decision
- practicability of EV-grid connection: e.g. required gear and resulting set-up time (e.g. cable vs. cable-free charging)
- safety considerations in terms of charging gear
- availability of non-electric fuel (PHEV)
- general availability of fast-charging (as convenient non-electric fuel alternative)

Behavioral factors

Driving behavior
- number of trips driven per day
- vehicle use frequency: e.g. daily, weekly, monthly
- departure and arrival places, dependent on:
  - household characteristics, e.g.: household type, age, economic status, occupation
- driven distance, driving time, parking time, dependent on:
  - way purpose, e.g.: work, education, shopping, leisure
  - Weekday

Connection & charging decision
- connecting probability upon arrival, dependent on
  - $SOC(t_{arrival})$
  - charging location
  - $P_{nominal}$ in kW
- uncontrolled charging upon arrival vs. user-controlled charging upon arrival or operator-controlled charging, dependent on
  - user strategy for setting $\widehat{SOC}\left(\hat{t}_{departure}\right)$
  - different target functions, e.g. minimizing charging costs/load peaks/CO2 emissions, maximizing revenues from ancillary services
  - different system perspectives, e.g. individual vs. system optimum



Spatial-technical factors

Expected market penetration of EVs
Expected market penetration of charging stations
  - at home
  - at work
  - in public: city parking lots, supermarkets, highways, etc.

Spatial-behavioral factors

Driving behavior
- influence of household‘s place of residence: e.g. city, urban, rural

Connection & charging decision
- security considerations in terms of charging location
- accessibility: e.g. time and distance to closest idle charging station

FIGURE 1: OVERVIEW OF INFLUENCING FACTORS ON ELECTRIC VEHICLE CHARGING

Technical domain

First of all, the most important technical aspects influencing electric vehicle charging is the energy consumption of the EV typically measured in kWh per 100 km. This quantity is physically dependent on e.g. the velocity profile, the rim size, the vehicle weight, the vehicles' aerodynamics and the use and application of auxiliary devices such as heating and cooling of the passenger cell or heating and cooling of the battery controlled by the battery management system. Furthermore, the maximum velocity and the total battery size (together with the usable battery share) as well as the self-discharging rate of the vehicle influence energy consumption and therefore the recharge frequency. Additionally, the nominal charging power of the electric vehicle's internal charger and the charging station's external charger together with their particular efficiencies primarily influence the charging time.

Several technical aspects influencing the connection and charging decision also relate to the behavioral domain such as the practicability of EV-gird connection in terms of required gear and resulting set-up time (e.g. cable charging vs. inductive charging). Also safety considerations in terms of charging gear may play a role. Additionally, the availability of non-electric fuel such as for PHEV and the general availability of fast-charging as convenient non-electric fuel alternative can impact connection and charging decisions.

3 Differentiation of households' driving behavior

This chapter provides an overview of the data being used to derive households' driving behavior differentiated by socio-economic, sociodemographic and temporal influencing factors. Subsequently, a broad range of statistical methods is used to identify effects on categorical and continuous dependent variables of interest before results are presented. In the final section a critical summary based on the conducted tests is drawn, allowing an answer to the first research question (cf. Section 1).

3.1 Data used

3.1.1 Mobility in Germany (MiD)

The survey data on mobility behavior of households in Germany commissioned by the Federal Ministry of Transportation and Digital Infrastructure (BMVI) form the empirical basis for the analysis in this section and for the subsequent modeling described in Section 4.
The applicability of the data selected for the present study is based on the assumption that driving behavior does not differ between drivers of EV cars and of cars with internal combustion engines (ICE). This follows from the underlying idea that mobility needs are robust in terms of transportation means.

The corresponding study, *Mobilität in Deutschland 2008* (MiD), was most recently conducted in Germany in 2008 and 2009 by Follmer et al. (2010*a*) with roughly 40,000 participating household members from approximately 26,000 households. The initial household data collection was conducted either as a paper and pencil interview (PAPI) or a computer assisted web interview (CAWI). The person and trip interviews in later stages were solely conducted as computer assisted telephone interview (CATI) allowing higher return rates and better data quality (Follmer et al., 2010*a*, p. 8). Currently a new inquiry for MiD 2016 is ongoing until May 2017. First study results are expected in late 2017.

The focus of the survey was to collect information on the *everyday mobility* behavior of private households for most transportation purposes, e.g. *leisure traffic*, *commuting* and *commercial transport*. In terms of access to transportation means it is not limited to *private/individual transportation*, e.g. the use of motorized vehicles like motorcycles or cars but also provides information on *public transportation* means, e.g. railway, bus or plane usage.

MiD data consists of two files for each of the following units of observation:
- *households*
- *persons* (household members)
- *vehicles*
- *trips* (covered one-way trips)
- *journeys* (vacation trips)

One file is the so-called Public Use File (PUF) and the other an Additional File (ZF) provided for specific analysis. The latter contains raw data except for some coding for missing data points, additional projection factors and *inverse Mil's ratios*, which can be used in multivariate statistical analysis to take account of possible *selection bias* (Follmer et al., 2010*b*, p. 45). The analysis conducted in this section as well as the modeling part in Section 4 are based upon the PUF datasets since the authors preliminarily examined the consistency of the data points by coding implausible values and resolving outliers. Like the ZF dataset the PUF datasets include *weighting coefficients* and provide additional derived analytical variables as well as external variables for a more detailed description of the spatial and settlement characteristics of each household (Follmer et al., 2010*b*, p. 12).

The *weighting coefficients* are used in the analysis as well as in the modeling part in Section 4 due to the data generating process of the survey: the data is based on a random sample of citizens from the German register of residents. The foundation of the MiD data is therefore a sample of persons. As all drawn persons originate from a registered German household and all household members of a drawn person's household were invited to participate in the survey, the sample of households directly results from the sample of persons, thereby leading to a underrepresentation of small households. *Weighting coefficients* therefore help to correct for the underlying spurious drawing probabilities of household and person attributes. This method works especially well for the attributes used in determining the *weighting coefficients* (namely: household size, age group, gender, differentiated regional type, weekday and month of the survey due day) and for variables with no or little nonresponse cases (Follmer et al., 2010*b*, p. 25). The steps for determining the final *weighting coefficients* can be described as follows:

1. Determination of design weights using the inverse selection probability (Horvitz–Thompson estimator) for all (i) federal states and (ii) all invited persons in the selected communities of each federal state

2. Nonresponse analysis and adjustment (i.e. multiplication of the person weights with the reciprocal of the share of actually participating invited persons)

3. Transformation of the person sample into a household sample (i.e. multiplication of the adjusted person weights with the reciprocal of the number of household members)

4. Post-stratification for both (i) households and (ii) persons (i.e. adjustment of sample weights to known and validated distributions of attributes in the population like gender, age, income, etc.)

Step number 4 reveals a possible reason why the effectiveness of applying these *weighting coefficients* is limited to the incorporated variables used for their determination. Since frequencies of all possible attribute levels in the population have to be known, additional variables lead to a combinatorial explosion of information required on the population[1].

The *household* dataset consists of 25,922 households of which 25,912 have no or at least one car available. 10 households didn't provide information on the availability of a car.
The *vehicle* dataset consists of 34,601 cars, all originating from participating households of the *household* dataset stated above.
The *trip* dataset consists of approx. 193,000 one-way trips of which approx. 70,000 were undertaken using households' cars and consisting of regular H-W or W-H trips and intermittent business trips. Additionally, the dataset contains 256 vacation trips and 8,856 regular job-related trips (rbW - *regelmäßige berufliche Wege*) executed during working hours, e.g. from craftsman, bus drivers, postmen, salesmen or distributors (Follmer et al., 2010*a*, p. 4). These are not included as they lack relevant numerical and categorical information. However, intermittent business trips remain in the dataset.
The *person* dataset consists of 58,131 household members of which 40,661 have a valid driving license and stem from households with at least one car available.

[1]Additional information, further reasoning and the particular steps for calculation are provided by Follmer et al. (2010*b*, p. 38–41)

An holistic overview on excluded data together with further explanations will be given in Section 3.1.3.

The datasets and comprehensive additional information, e.g. a user guide, the final as well as a methodical report, variable overviews, coding plans and a series of tables are publicly obtainable for scientific and educational purposes from Clearingstelle für Verkehr, Deutsches Zentrum für Luft- und Raumfahrt e.V. (2017).

3.1.2 Comparison with other German mobility studies

Other major mobility surveys for Germany like the cross-sectional study *Kraftfahrzeugverkehr in Deuschland 2010* (KiD) focus on commercial transportation (Wermuth et al., 2012, p. 15) or aim at identifying temporal changes in mobility behavior like the longitudinal study *Deutsches Mobilitätspanel* (MOP) (Weiss et al., 2014, p. 13), whose total household sample size over all inquiries since 1994 is approx. of the same size as the MiD 2008.

Even though all mentioned major mobility studies report steadily changing mobility indicators over time, the changes between different years and different studies with regard to the same unit of observation are relatively small: the average trip length without regard to transportation means, for example, increased for MiD from 11.7 km in 2002 to 11.8 km in 2008 and for MOP from 11.0 km to 11.7 km in the same time (Follmer et al., 2010*a*, p. 21).

An important difference between MiD and MOP is, however, due to the fact that the MOP dataset consists of information collected over a time span of one week for *persons* and 8 weeks for *vehicles*, while the MiD data were only recorded for single days of a particular household on all levels of observation. This prevents an analysis of regularities or irregularities of mobility behavior over time horizons beyond a daily resolution, for example how persons use a household's car over a full week.
For MiD it is therefore necessary to assume that the individual household's survey due day reflects the typical behavior of that household also on a weekly, monthly or annual horizon.

A central distinction between MiD and KiD is due to the fact that KiD provides detailed temporal and spatial information on trips related to commercial transportation

(Wermuth et al., 2012, p. 54) which would allow a better representation in simulation models geared to real driving behavior. Although MiD records similar information (cf. abbreviation rbW above) as part of the *person* interviews it is primarily limited to categorical or count data, e.g. used main transportation means per rbW-trip and number of rbW-trips on the survey due day. Numerical information is available but limited in terms of informative value, e.g. the estimated total covered distance of all rbW-trips in km, which is uniformly distributed over all executed rbW-trips per person. Temporal and spatial information about rbW-trips are not included or derivable from the *trip* dataset.

In summary, the MiD dataset provides solid information on *everyday mobility* of ICEV drivers together with a comparably high sample size as to the combined MOP data since 1994. It further avoids the incorporation of temporal mobility trends (as it would be for MOP) into the data basis for the BEV simulation model explained in Section 4. However, its external validity concerning rbW-trips (or in other words: with respect to the *commercial transportation* domain) is limited.

3.1.3 Data preparation

As a first step 10 households, that did not report any information on the availability of cars, as mentioned before, are excluded from the *household* dataset. The original *vehicle* dataset could be used without any further preparation.
Concerning the *trip* dataset all 8,856 rbW-trips were primarily excluded from the approx. 193,000 originally available entries since they lack the information required to calculate the numerically dependent variables presented in the next section (cf. last paragraph of Section 3.1.2). After that, 75 remaining double entries based on equal values for all 124 available columns except for the unsorted and sorted trip counter variables per person (*wid* and *wsid*) were removed from the dataset. Subsequently the counter variables were recalculated for consistency reasons. Likewise, entries which represented vacation trips were removed from the *trip* dataset and correspondingly all entries from the *person* dataset as well. A consistency test on the resulting datasets yielded that either all or no trips of a person had been excluded by this procedure. After that, the *trip* dataset was restricted to trips by persons originating from households with at least one car available, thereby excluding approx. 10,000 entries. A further restriction on trips entirely executed with one of the household's cars while also providing valid spatial information about the point of departure

and destination excluded over 100,000 trips executed by other means of transportation. In a final step 399 trips, where other household members reported themselves as the driver were excluded resulting in the final *trip* dataset with approx. 70,000 valid data points.

Subsequently, available numerical information on driving time, driven distance, average speed and parking time were refined. To this end, it was first reviewed if the author's of the study correctly calculated the driving time derived from the reported departure and arrival times (cf. Figure 49 in A.1.1), which was the case. However, for two trips the recalculation lead to negative driving times since the originally reported arrival time was before the departure time. Two other entries of the resulting *trip* dataset exceeded 16 hours of driving time, which was regarded as implausible in the context of this work. Consequently, these entries were excluded.

In a next step the individual minute values of the driving time as well as the parking time were assigned to 5 minute time steps since a lot of data points accumulated on values with a right-hand digit of 0 or 5. This denotes a general uncertainty of the respondent to precisely report numeric data due to simplifying heuristics as it is typical for survey data. The minimum resolution of all temporal variables used can therefore, at best, be defined in 5 minute time steps. Another methodological adaption that allows for the respondent's uncertainty will be given in Section 4.1.3.

After that, entries with missing or zero driven distance values were assigned to groups of the same driving time step, and replaced with the average driven distance of the corresponding driving time step group. This was the case for 162 dataset entries.

Having refined the driving time and the driven distance in a direct way, they were subsequently indirectly refined using the average speed. Based on the survey results of EARSandEYES (2008) regarding the maximum driving speed on German highways, average speeds higher than 180 km per hour were deemed to be implausible. The same applies to trips with average speeds lower than 3.9 km per hour. This threshold was determined by a detailed examination on the first quantile of the average speed distribution before data preparation (cf. Table 3). It revealed that an average speed of 3.9 km per hour can be regarded as plausible in special congestion situations. In comparison, in 2016 the lowest average speed for congestion in Germany measured by Cookson and Pishue

(2017, p. 34) was 9.9 km per hour. For that matter, the driving time as well as the driven distance were replaced with the corresponding moving average, determined as the mean of the three driving time step groups prior to the group of the value in doubt. This was the case for 1,525 observations.

Table 3 shows typical location parameters of the driving time, driven distance and average speed of all car trips before and after exclusions and refinements. Note that rbW-trips did not affect the parameters in the first place as they did not provide valid values for the numerical variables of interest.

TABLE 3: DRIVING TIME, DRIVEN DISTANCE AND AVERAGE SPEED OF ALL CAR TRIPS BEFORE AND AFTER DATA PREPARATION

Dependent variable	**Status**	**Min.**	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
Driving time	Before	1.00	10.00	15.00	20.67	25.00	480.00
in 5min	After	1,00	10.00	15.00	20.29	25.00	875.00
Driven distance	Before	0.00	2.38	5.70	15.15	14.25	950.00
in km	After	0.10	2.76	5.70	13.33	14.25	864.00
Average speed	Before	0.50	17.10	27.69	31.00	41.00	247.00
in km/h	After	3.90	17.10	28.50	31.33	41.80	175.30

Besides exchanging various attributes between the *household*, *car* and *trip* datasets by simply joining the respective tables on specific keys, the exact reconstruction of spatial information for every trip posed a bigger challenge. For that matter, information, gathered by taking a combined look on the departure place, destination and trip purpose variables from the *trip* dataset outlined in the appendix (cf. A.1), were used. Using systematic reasoning, most trips of each participating person were assigned to one of the following 16 *departure place – destination* pairs, while maintaining logically consistent sequences for all departure and arrival places of a person on the survey due day (cf. Figure 2):

- H-H: departure at 'home' with destination 'home'
- H-W: departure at 'home' with destination 'workplace'
- H-I: departure at 'home' with destination 'somewhere inside own city or town'
- H-O: departure at 'home' with destination 'somewhere outside own city or town'
- W-H: departure at 'workplace' with destination 'home'
- W-W: departure at 'workplace' with destination 'workplace'
- W-I: departure at 'workplace' with destination 'somewhere inside own city or town'

- W-O: departure at 'workplace' with destination 'somewhere outside own city or town'
- I-H: departure 'somewhere inside city' with destination 'home'
- I-W: departure 'somewhere inside city' with destination 'workplace'
- I-I: departure 'somewhere inside city' with destination 'somewhere inside own city or town'
- I-O: departure 'somewhere inside city' with destination 'somewhere outside own city or town'
- O-H: departure 'somewhere outside own city or town' with destination 'home'
- O-W: departure 'somewhere outside own city or town' with destination 'workplace'
- O-I: departure 'somewhere outside own city or town' with destination 'somewhere inside own city or town'
- O-O: departure 'somewhere outside own city or town' with destination 'somewhere outside city'

All pairs were combined in a new variable. In the end is was possible to enrich 68,421 out of 69,970 car trips in the prepared *trip* dataset with this type of spatial information.

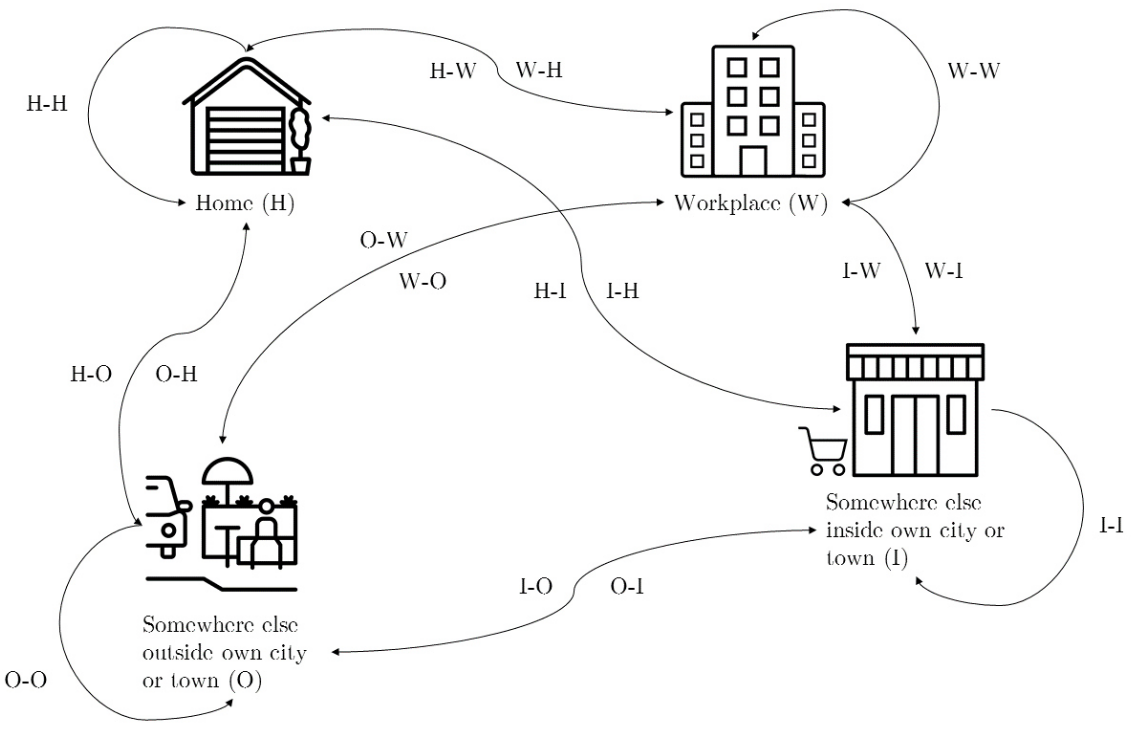


Figure 2: Determinable spatial information from the MiD trip dataset used to create logically consistent sequences of departure and arrival places

Building on this information, a further variable was added to the dataset specifying three different *trip distance categories* for each trip:

- inside city: assigned to all trips with *departure place* – *destination* pairs H-I, I-H, I-I
- outside city: assigned to all trips with *departure place* – *destination* pairs H-O, I-O, O-H, O-I
- unknown: assigned to all trips with *departure place* – *destination* pairs H-H, H-W, W-H, W-W, W-I, W-O, I-W, O-W, O-O

The residual category ‘unknown’ contains observations, where it was not possible to determine the precise location of the trip. It is, for example, unknown, whether the work place of a participating person is located inside or outside their own city or town (cf. A.1). Similarly, driven routes for H-H, W-W and O-O trips were not determinable.

In order to differentiate between different trips over one day the variable *trip index* was added to the trip dataset. The following levels were created:
- between: assigned to all trips between the first and the last trip of the day
- first: assigned to the first trip of the day
- firstANDlast: assigned to all trips driven on a day with only one trip
- last: assigned to all trips with only one

Regarding the vehicle dataset, an important variable called *main user (daily vehicle) use* with two factor levels *use* or *disuse* was added. This variable contains the information whether the primary driver of a household’s vehicle used it on the respective household’s survey due day. A *use* was defined as a day on which the vehicle drove a minimum of one trip. A *disuse* was defined as a day on which the vehicle drove no trips at all.
This variable provides the basis for the analysis of regularities or irregularities of driving behavior over time horizons beyond a daily resolution at least on average, i.e. combining the information of many households’ survey due days. However, it is worth noting that the informative value of an average consideration of daily vehicle use is limited as it does not reflect the certainly complex dependencies. For example, different households might have different weekly use patterns and some households might not have a weekly use pattern at all. In fact, this limitation applies to all variables of the MID dataset as it only provides information on the mobility behavior of households for single days (cf. MOP vs. MID in

Section 3.1.2).

3.1.4 Selection of dependent variables and MiD datasets

In preparation of the analysis is was necessary to choose relevant MiD datasets of interest. For this purpose, possible variables that describe mobility behavior outlined in Section 2.4 were selected from the MiD datasets.
In detail, the dependent variables presented in Tables 4, 5, 6 and 7 were chosen and analyzed within the context of the first research question. One can see that they relate to the *household*, *car* and to the *trip* datasets. The MiD *person* dataset is not analyzed directly, but instead provided *person* attributes to enrich the *car* or *trip* dataset. For example the occupation and vehicle use frequency of a household's car's primary driver were merged to the other datasets (see A.1.2 for further information on variable values). The *journey* dataset was not used for the following analysis or any other purpose in this work.

The variable nomenclature used in the rest of this thesis first indicates the unit of observation, e.g. 'HL' for 'household level' in front of the hyphen. After the hyphen, the statistical unit of the dependent variable is mentioned, e.g. 'N' for 'numerical', together with a counter for the related dependent variable. 'VL-C3' therefore specifies the third categorical dependent variable of interest on the level of vehicles.

Table 4: Analyzed numerical and categorical dependent variables (household level)

<table>
<tr><th>MiD dataset</th><th>Statistical data type</th><th>Coding</th><th>Dependent variable
(level of measurement)</th><th>Domain</th></tr>
<tr><td rowspan="4">Households</td><td>numerical</td><td>HL-N1</td><td>Number of cars
(interval/ordinal)</td><td>$1, \ldots, 8$</td></tr>
<tr><td rowspan="3">categorical</td><td>HL-C1</td><td>Economic status
(ordinal)</td><td>very high
high
medium
low
verylow</td></tr>
<tr><td>HL-C2</td><td>Household type
(nominal)</td><td>1A1830
1A3060
1A60p
SP
2A1mCu6
2A1mCu14
2A1mCu18
2Ay1830
2Ay3060
2Ay60p
3mA</td></tr>
<tr><td>HL-C3</td><td>Place of residence
(nominal)</td><td>rural
urban
city</td></tr>
</table>

For further information on categorical variable values, see Section 3.1.3 and A.1.2 .

Table 5: Analyzed numerical and categorical dependent variables (vehicle level)

MiD dataset	Statistical data type	Coding	Dependent variable (level of measurement)	Domain
Vehicles	numerical	VL-N1	Number of trips per (use) day (interval/ordinal)	$1, \ldots, 17$
	categorical	VL-C1	Main user occupation (nominal)	apprentice fulltime halftime homemaker pensioner student unemployed
		VL-C2	Main user (vehicle) use frequency (ordinal)	daily weekly rarely
		VL-C3	Main user (daily vehicle) use (ordinal)	use disuse

Note that ‘main user’ stands for the primary driver of a household’s vehicle.

Note that ‘(use) day’ stands for a vehicle that drove minimum one trip on the respective day (VL-C3 = ‘use’).

For further information on categorical variable values, see Section 3.1.3 and A.1.2 .

Table 6: Analyzed numerically dependent variables (trip level)

MiD dataset	Statistical data type	Coding	Dependent variable (level of measurement)	Domain
Trips	numerical	TL-N1	Driven distance in km (interval/ordinal) *H-W or W-H trips only*	$\mathbb{R}_{>0}$
		TL-N2	Driven distance in km (interval/ordinal) *all trips except H-W or W-H trips*	$\mathbb{R}_{>0}$
		TL-N3	Departure time of the first trip per day in 5min (interval/ordinal) *H-W trips only*	$\mathbb{N}_{\geq 1}$
		TL-N4	Departure time of the first trip per day in 5min (interval/ordinal) *all trips except H-W trips*	$\mathbb{N}_{\geq 1}$
		TL-N5	Driving time in 5min (interval/ordinal) *H-W or W-H trips only*	$\mathbb{N}_{\geq 1}$
		TL-N6	Driving time in 5min (interval/ordinal) *all trips except H-W or W-H trips*	$\mathbb{N}_{\geq 1}$
		TL-N7	Parking time in 5min (interval/ordinal) *H-W trips only*	$\mathbb{N}_{\geq 1}$
		TL-N8	Parking time in 5min (interval/ordinal) *all trips except H-W trips*	$\mathbb{N}_{\geq 1}$

For further information on categorical variable values, see Section 3.1.3 and A.1.2 .

Table 7: Analyzed categorical dependent variables (trip level)

MiD dataset	**Statistical data type**	**Coding**	**Dependent variable (level of measurement)**	**Domain**
Trips	categorical	TL-C1	Departure arrival place: 'from...to' (nominal)	H-H H-W H-I H-O W-H W-W W-I W-O I-H I-W I-I I-O O-H O-W O-I O-O
		TL-C2	Trip purpose (nominal)	accompanying business education errand leisure shopping work

For further information on categorical variable values, see Section 3.1.3 and A.1.2 .

3.2 Statistical methods used

3.2.1 Categorical data

The influence of different factors on the selected categorical dependent variables (cf. Table 4, 5 and 7) was analyzed using a combined graphical and inferential statistical method, namely *residual-based shading for visualizing (conditional) independence* (Zeileis et al., 2007). This approach uses inferential information on the independence (and deviation from independence) from a χ^2-*Test of Independence* for two-way contingency tables, information on the conditional relative frequencies of the attribute levels being explained and marginal relative frequencies of the explanatory attribute levels and graphically displays the results in so-called *mosaic plots*. The implementation was done in R (R Core Team, 2017) using the 'vcd' package from Meyer et al. (2016). This section provides important background information for interpreting the results presented in Section 3.3.

Contingency tables summarize data by counting the number of observations for all attribute levels of the involved variables. Using the sample proportions of each attribute level the attribute levels' probabilities are estimated. Suppose there is a categorical explanatory variable, denoted by X and a categorical variable Y being explained. Let I denote the number of attribute levels of X and J the number of attribute levels of Y. A rectangular table with I rows for all attribute levels of X and J columns for all attribute levels of Y has so-called *cells* that display counts of $I \cdot J$ possible attribute levels' combinations. A table of this form with two variables of interest is called a *two-way contingency table.* A three-dimensional table would be called a *three-way contingency table*, etc. (Agresti, 2007, p. 21f)

Calculated probabilities from contingency tables can be of three types - *joint*, *marginal* or *conditional.* Let $\pi_{ij} = P(X = i, Y = j) = p_{ij} = n_{ij}/n$ denote the probability that an observation (X, Y) falls in the cell in row i and column j of the contingency table where n_{ij} denotes the cell counts of row i and column j and $n = \sum\limits_{i,j} n_{ij}$ the total number of observations. The probabilities $\{\pi_{ij} | i = 1, ..., I, j = 1, ..., J\}$ form the *joint distribution* of X and Y. Like every discrete distribution of random variables they satisfy $\sum\limits_{i,j} \pi_{ij} = 1$. The *marginal distributions* are the row-wise and column-wise sums of the joint distributions. For a two-way contingency table $\pi_{1+} = \pi_{11} + \pi_{12}$ and $\pi_{2+} = \pi_{21} + \pi_{22}$ form the marginal distribution for the row variable. Accordingly, $\pi_{+1} = \pi_{11} + \pi_{21}$ and $\pi_{+2} = \pi_{12} + \pi_{22}$ for the column variable. Thereby, the subscript '+' denotes the sum over the index it replaces.

(Agresti, 2007, p. 22)
The *conditional probability* $\pi_{i|j} = P(X = i|Y = j) = p_{i|j} = n_{ij}/n_j$ denotes the probability that an observation X falls in the cell in row i given that $Y = j$ is already known where $n_j = \sum_i n_{ij}$ denotes the number of observations of column j. The conditional probabilities $\{\pi_{i|j} \; |i = 1, ..., I\}$ form the *conditional distribution* of X given that $Y = j$.

Statistical independence of two categorical variables is given if the probability that X falls in row i and Y falls in column j is the product of the probability that X falls in row i with the probability that Y falls in column j:

$$\pi_{ij} = \pi_{i+} \cdot \pi_{+j} \text{ for all } i = 1, ..., I \text{ and } j = 1, ..., J \tag{3.1}$$

That means, that all joint probabilities are equal to the product of their marginal probabilities. (Agresti, 2007, p. 25) Expressed using the *conditional probability* one obtains:

$$\pi_{i|j} = \pi_{i+} \text{ or } \pi_{j|i} = \pi_{+j} \text{ for all } i = 1, ..., I \text{ and } j = 1, ..., J \tag{3.2}$$

These expressions provide a sufficient condition for statistical independence being the equality of all conditional and marginal probabilities.
Likewise, two categorical variables are *conditionally independent* given a third variable $Z = z$ if the conditional probability $\pi_{ij|z}$ is the product of the conditional probabilities $\pi_{i+|z}$ and $\pi_{+j|z}$ for all $i = 1, ...I$ and $j = 1, ..., J$.

Mosaic plots visualize relative frequencies instead of Pearson residuals, which are typically illustrated by *association plots*. A typical mosaic plot for a two-way contingency table (cf. Fig. 3) consists of a set of several tiles with areas proportional to the observed cell frequencies. A rectangle corresponding to one cell is first split horizontally with respect to the *marginal* relative frequency for its attribute level related to the variable shown on the x-axis and then vertically with respect to the *conditional* relative frequency of the attribute level related to the variable shown on the y-axis, given its previously split attribute level. From Equation 3.2 one can deduce that the rectangle's width has to be identical for all tiles of a column if the data at hand provide evidence for a perfect statistical independence of the involved variables. For Figure 3 this is not the case, indicating a strong statistical dependency between being actually treated or getting a placebo and the improvement of the treatment. (Agresti, 2007, p. 510)

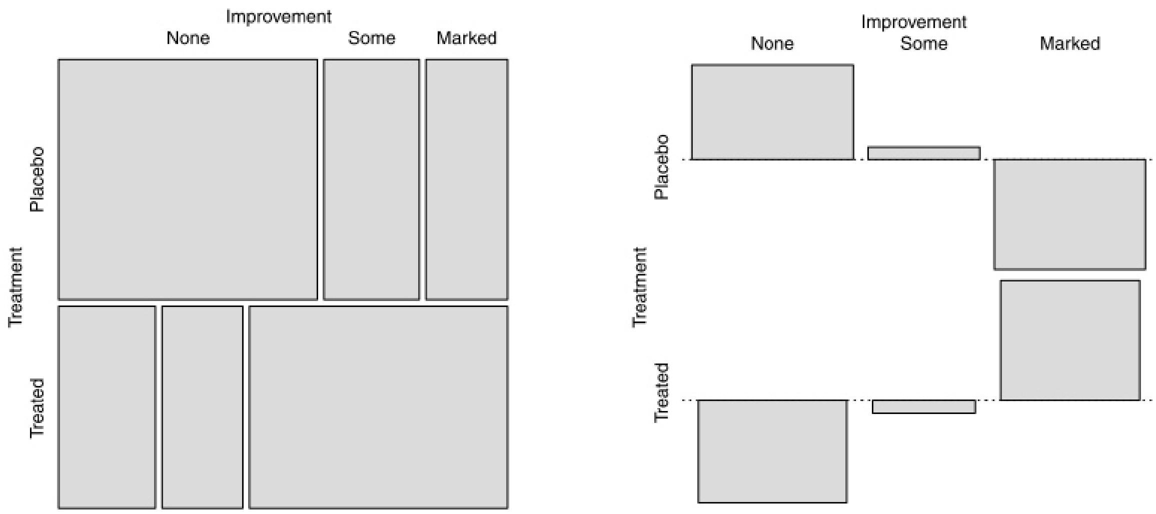


FIGURE 3: UNSHADED MOSAIC (LEFT) AND ASSOCIATION PLOTS (RIGHT) FOR EXAMPLE DATA (ZEILEIS ET AL., 2007, P. 511)

The χ^2-*Test of Independence* (Agresti, 2007, p. 34–37) for two-way contingency tables tests the hypothesis that two variables are statistically independent. Therefore one denotes for the null hypothesis:

$$H_0 : \pi_{ij} = \pi_{i+} \cdot \pi_{+j} \text{ for all } i, j \in \{1, 2\} \tag{3.3}$$

For a sample size of n with cell counts $\{n_{ij}\}$, the values $\{\mu_{ij} = E(n_{ij}) = n\pi_{ij}\}$ are the *expected frequencies* assuming that H_0 is correct. Since the the 'real' values of μ_{ij} for the given population are typically not known, one estimates the expected frequencies from the sample at hand:

$$\hat{\mu}_{ij} = np_{i+}p_{+j} = n\left(\frac{n_{i+}}{n}\right)\left(\frac{n_{j+}}{n}\right) = \frac{n_{i+}n_{+j}}{n} \tag{3.4}$$

In order to decide whether the sample data contradict H_0 one compares $\{n_{ij}\}$ to $\{\hat{\mu}_{ij}\}$. In case the differences $\{|n_{ij} - \hat{\mu}_{ij}|\}$ are large , one rejects H_0 on the basis of the sample data at hand and the chosen significance level. If n_{ij} is close to μ_{ij} for each cell one concludes the opposite. Further information on the requirements for a valid rejection will be given later.

In 1900 Karl Pearson proposed a corresponding test statistic making use of the fact that it is asymptotically chi-squared distributed with $k \in \mathbb{N}_{>0}$ *degrees of freedom* (df):

$$X^2 = \sum \frac{(n_{ij} - \hat{\mu}_{ij})^2}{\hat{\mu}_{ij}} \overset{d.a.}{\sim} \chi^2(k) \tag{3.5}$$

For $(I \times J)$-tables $k = (I-1)(J-1)$ because under the null hypothesis there are $(I-1)+(J-1)$ nonredundant (i.e. a cell probability that can not be expressed by other row or column probabilities using $\sum_i \pi_{i+} = 1$ and $\sum_j \pi_{+j} = 1$) row and column probabilities $\{\pi_{i+}\}$ and $\{\pi_{+j}\}$. Correspondingly, for the alternative hypothesis H_1 there are $IJ-1$ nonredundant row and column probabilities. k therefore results in the difference between the number of parameters under H_1 and H_0:

$$k = (IJ-1) - [(I-1)+(J-1)] = IJ - I - J + 1 = (I-1)(J-1) \tag{3.6}$$

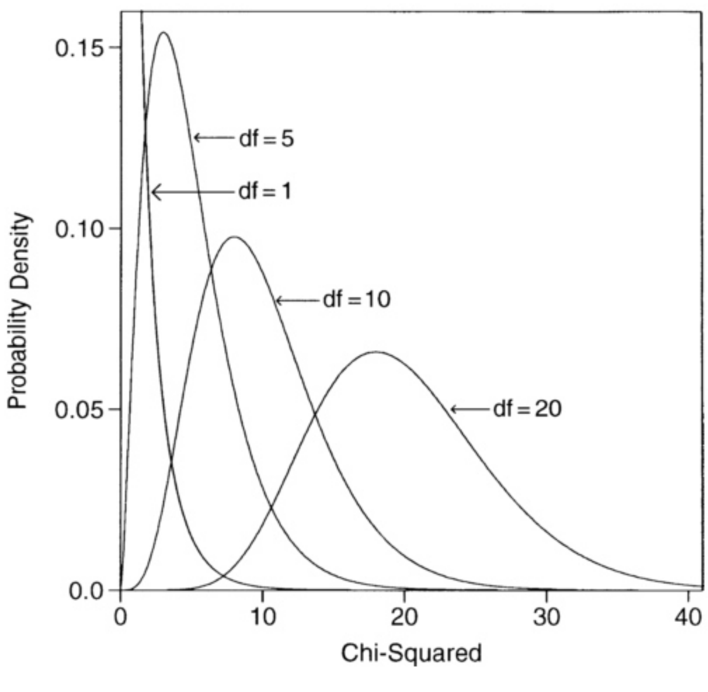


Figure 4: Examples of probability density functions of chi-squared distributions (Agresti, 2007, p. 35)

Figure 4 shows probability density functions (PDF) of χ^2 distributions for different values of k. From that it is possible to determine the probability to observe a specific or more extreme value of X^2, the so-called *p-value*. If the p-value is smaller than a predefined *level of significance* α (i.e. the probability to falsely reject the null hypothesis although H_0 is actually true) one speaks of a *significant* test result which leads to the rejection of the null hypothesis based on the given data with a certainty of α. This indicates that the data at hand provide evidence for a specific effect (defined by the mathematical form of test statistic and hypotheses) which is not only rooted in chance.

For the χ^2-Test of Independence another (more statistically powerful) test statistics, the *Likelihood-Ratio Statistic* G^2, exists, but as it shares "many properties and usually provide the same conclusions" (Agresti, 2007, p. 36) compared to Pearson's X^2 and Zeileis et al. (2007) use the latter, it will not be outlined within the limits of this work.

Similarly, different mathematical expressions exist to quantify the deviation from independence (*residuals*) for each cell in a contingency table: Agresti (2007, p. 38) introduce *standardized residuals* dividing the numerator from Equation 3.5 by its standard error, whereas Zeileis et al. (2007, p. 509) present *Pearson residuals* following Equation 3.5 as well as the *maximum Pearson residual*, which is the maximum of the Persons residuals of all cells:

$$M = \max_{i,j} \frac{|n_{ij} - \hat{\mu}_{ij}|}{\sqrt{\hat{\mu}_{ij}}} \tag{3.7}$$

Zeileis et al. (2007, p. 509) state that without further specifications of a 'certain pattern of independence [...] no functional [form] uniformly dominates all others in terms of test power. Therefore, the choice of the functional [form] is usually guided by the data analysis problem at hand'. For further information on statistical power, see Ellis (2010).
Zeileis et al. (2007, p. 515–517) analyzed both Pearson residuals as well as maximum Pearson residuals to introduce a better shading scheme for *mosaic plots* making use of typical significance levels $\alpha = 0.1$ and $\alpha = 0.01$ for the data at hand in contrast to hard-coded test statistic cut-offs at the critical values 2 and 4 of Friendly (1994).
For the *residual-based shading* applied throughout this work, maximum Pearson residuals were used since they visualize and highlight the significance (if any) of mosaic plot's tiles and the corresponding cell frequencies that are most 'responsible for the dependence' (Zeileis et al., 2007, p. 509). The cut-offs for the shading (see legend at the right hand side of Figure 5) therefore represent critical values of the test statistic at the two significance levels stated above.

Like any significance test, also the χ^2-*Test of Independence* has limitations which have to be carefully reviewed. First, the test alone cannot provide information on the direction and magnitude of an association. However, this is prevented by combining the test results with a residual-based shaded mosaic plot allowing to study the nature of the association by evaluating relative frequencies and residuals. Figure 5 shows the shaded mosaic plot of the example data from Figure 3 using the maximum Pearson residuals with significance levels $\alpha = 0.1$ (reduced color) and $\alpha = 0.01$ (full color). It can be seen, that patients who received the 'placebo' were considerably less likely to have a 'marked' improvement compared to patients who have been "treated" and that these two groups are most certainly responsible for the significance of the statistical dependency between the variables 'treatment' and 'improvement'.

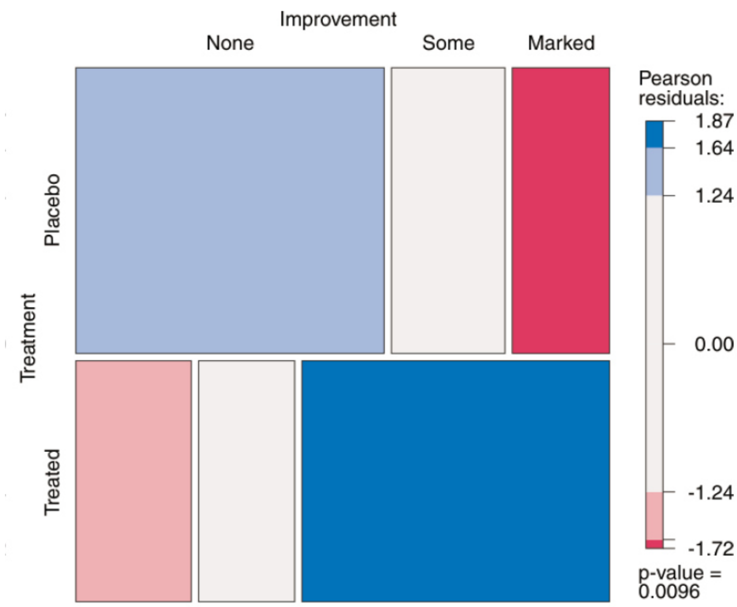


Figure 5: Shaded mosaic plot for example data (Zeileis et al., 2007, p. 516)

Second, the X^2 statistic requires large samples to be asymptotically $\chi^2(k)$ distributed. The approximation is particularly poor if some cell frequencies are less than 5 while the overall sample size is relatively small. Third, the power of the test (also called sensitivity, i.e. the probability that the test correctly rejects the null hypothesis when the alternative hypothesis is actually true), which positively depends on sample size (Ellis, 2010), can be increased when at least one variable is ordinally scaled. For proposed adjustments to the test, see Agresti (2007, p. 41ff). Because the sample sizes of the MiD data at hand (cf. Section 3.1) are very large (as long as the number variables of interest with multiple attribute levels is limited to two or three), compared to e.g. clinical trials or specific sociological studies that often provide barely up to 100 participants, both the limitation on sample size as well as possible refinements related to statistical power can be neglected in favor of a more common statistical method (Agresti, 2007, p. 40).

More complex statistical methods used to model associations of multiple categorical variables of interest like the *Generalized Linear Model* (GLM) or particularly its special cases for binary as well as multi categorical responses, namely *Logistic regression* (also known as *Logit Models*), and *Loglinear Models* used to model multi-way contingency tables were beyond the scope of this work and particularly made difficult due to highly multi-categorical data for the sample sizes at hand. The interested reader may consult Agresti (2007, p. 65ff, 99ff, 173ff, 204ff) for further information on modeling and analyzing categorical data using the above mentioned methods.

For assessing the magnitude of a dependency, a typical nominal *effect size measure* for two-way contingency tables, namely *Cramer's V*, was used throughout this work. This effect size measure is computed by taking the square root of the χ^2-statistic divided by the total sample size n and the minimum of $I - 1$ and $J - 1$:

$$V = \sqrt{\frac{\chi^2/n}{min(I-1, J-1)}} \tag{3.8}$$

V ranges from 0 indicating no association at all and 1 indicating a complete association between the involved variables.

3.2.2 Numerical data

The data analysis problem at hand is limited to the following question: how can it be statistically inferred that a categorical independent variable (factor) has an influence on a numerical response variable?

Classical methods providing an answer to this question concentrate on comparing location parameters of factor levels, e.g. group means as it is the case for *Student's two-sample t-tests* and the *One-way Analysis of Variance* (ANOVA) or aim at comparing regression coefficients of dummy variables representing different factor levels as is the case for *Linear Regression* (LR). These methods are part of the so-called *parametric statistics*, which assumes that sample data comes from a population that follows to a certain extent a specific probability distribution based on a fixed set of parameters (Geisser and Johnson, 2006).

Others, particularly *non-parametric methods*, concentrate on comparing quantities related to the whole empirical distribution of the response variable as it is the case for the *Kolmogorov–Smirnov test* (KS) or rank-based test like the *Wilcoxon-Mann-Whitney test* (for factors with two levels) or the *Kruskal-Wallis test* (for factors with more than two levels).

As stated before all these methods (like any other inferential statistical test) make assumptions about the structure of the underlying data that have to be carefully reviewed before drawing conclusions from the test results. A detailed introduction to all mentioned methods would be beyond the scope of this work, but comparing their assumptions (cf. Table 8) and properties in the context of the data and the hypotheses at hand give reasons for the application of the *non-parametric* (ordinal) method from Norman Cliff (Cliff, 1996, p. 123ff; Wilcox, 2015, p. 352ff; Wilcox, 2012, p. 180ff).

First, ordinal methods can provide more direct answers to typical research questions in behavioral research than parametric methods can (Cliff, 1996, p. 131). The goal of the conducted analysis was to generate information on empirical driving behavior capable to be incorporated in a stochastic simulation model. As such a model naturally relies on distributions of random variables, statements on a general effect of an influencing factor are of higher interest for the conducted analysis than comparisons of location parameters (e.g. means) since conclusions drawn from latter tests can be misleading compared to tests taking information of the distribution of the data into account. For example, the distribution of a numerical response variable can have a mode at lower values for one factor level group than for another but have a long tail in the direction of higher values whose extreme values make the order of the means opposite to that of most values. To further illustrate this example let Y_1 and Y_2 be two samples of a dependent variable of interest with the size $n_1 = 10$, $n_2 = 15$ for two different factor levels $X_1 = 1$, $X_2 = 2$:

$$Y_1 = \{1.0, 1.4, 1.5, 2.0, 2.0, 2.0, 7.0, 8.0, 9.0, 10.0\} \tag{3.9}$$

$$Y_2 = \{1.6, 1.8, 2.0, 2.1, 2.2, 2.7, 2.7, 2.8, 2.9, 2.9, 2.9, 3.0, 3.1, 3.2\} \tag{3.10}$$

The corresponding sample means are $\bar{Y_1} = 4.39$, $\bar{Y_2} = 2.63$ whereas the modes (i.e. the most frequent value) are $Y_{M1} = 2.0$ and $Y_{M2} = 2.9$. This conflictive description of the data results from the heavy-tailed observations of the first sample.
In general it is better to rely on more general characterizations of effects, e.g. the prob-

ability that values of the second group are higher than in the first group, denoted by $P(Y_2 > Y_1)$. This rather relates to questions like 'Does factor level 1 tend to have higher values for Y than factor level 2?' than to 'How do factor level 1 and 2 differ on average regarding y?'. Methods testing ordinal hypotheses are naturally better suited to provide answers to these kind of questions with an ordinal character and in the context of this work particularly suitable for providing information for a stochastic simulation model.

Second, which is perhaps the most often cited reason for choosing ordinal methods, they provide better *robustness* (in comparison to the distributional features of parametric methods), *resistance* (in a more descriptive sense of being less influenced by outliers) and *test power* (in cases when the prerequisites of parametric methods are not fully met) (Cliff, 1996, p. 1). Even though Vargha and Delaney (1998, p. 186) warn to use non-parametric methods (using the example of the *Kruskal-Wallis test*) just because "the side conditions of the corresponding parametric comparison tests (two-sample t test and ANOVA) are violated" they conclude to use robust alternatives which can be non-parametric methods, but with the requirement to carefully review their assumptions as well. For example, in case the assumption of homoscedasticity (i.e. the equality of variances upon factor level groups) is not met, the null hypothesis of the *Kruskal-Wallis test* does not longer test the equality of expected values but stochastic homogeneity which is equivalent to the equality of the rank mean expected values (Vargha and Delaney, 1998, p. 178).
In general Cliff (1996, p. 128) states on the robustness and power that "ordinal methods sacrifice a little power when circumstances are optimal for the normal-based ones, but often have greater power, sometimes substantially greater, when classical assumptions are violated. In addition, they are more robust in that their nominal alpha levels are more realistic than normal-based methods in a wide variety of circumstances."
Table 8 shows that all classical methods assume $Var(Y_i) = Var(Y_j)$ for all $i, j \in \{1, \ldots, p\}, i \neq j$ (i.e. homoscedasticity) except for the *Two-sample Kolmogorov-Smirnov test* which is on his part not able to answer the specified research questions of Section 3.3 regarding numerically dependent variables because the direction of an effect is not determinable from the test statistic, which is usually used to assess the effect size.
In order to check on homoscedasticity, the *Brown-Forsythe test* which is outlined in the next paragraph was conducted. Results presented in A.2 (cf. Table 12–17) show that the data at hand is heteroscedastic for the majority of factors even under different types of transformations. In this case some methods offer viable robust alternatives, like Welch's

t-test, Welch's ANOVA or robust regression techniques. Even though these methods proved to be more robust in terms of controlling the type I error rate (i.e. the rate of incorrectly rejecting a true null hypothesis) in the presence of heteroscedasticity, they can often result in a dramatic increase in the type II error rate (i.e. the rate of incorrectly retaining a false null hypothesis) and therefore result in a considerably lower statistical power, particularly when other important assumptions like normality within groups or normality of the error terms are not met (Wilcox, 2015, p. 327). Figures 61 and 62 in B.1 show that the numerically dependent variables at hand are all left skewed, some with long tails for higher values. For that matter it is common to resort to the *central limit theorem* (CLT) and rules of thumb for its validity in terms of sample size, but this neglects the modern insight that its convergence can be slow under these circumstances so that hundreds or even thousands of observations would be needed to obtain a good control of error rates (Wilcox, 2015, p. 328). Even though sample sizes of the MiD data at hand are relatively high for most factor level groups, this is not be the case when controlling for another factor level in order to analyze *interaction effects* (i.e. that the effect of one factor on the response variable also has an influence on the effect of another factor). For that reason the application of two-sample t-tests, one-way ANOVA or linear regression was abandoned in the context of this analysis. The Kruskal-Wallis and Wilcoxon-Mann-Whitney test were excluded in favor of *Cliff's method* because the latter provides a direct and well interpretable measure of effect size together with its test statistic (Cliff, 1996, p. 132). Further information on that will be given later in this section (cf. paragraph *Cliff's method for two independent groups*).

Third, another common reason for choosing ordinal methods derives from the presumed scale properties of the data (Cliff, 1996, p. 129). In behavioral research many variables have only ordinal justification. Even though the numerically dependent variables of interest from Section 3.1 (cf. Table 4, 5 and 6) are interval-scaled there is generally no concern in terms of power for using ordinal methods on interval-scaled variables when the prerequisites of the non-parametric methods are not fully met as outlined above.

Table 8: Overview of classical statistical methods used to infer that a categorical factor X with p levels has an influence on a numerical response variable Y

Method	Assumptions for inference	Possible adjustments and (robust test alternatives)	Multiple comparison problem	Typical effect size measure
Student's two-sample t-test	• $Y_i \overset{i.d.}{\sim} Y_j$ • $n_i = n_j$ • $Y_i \sim N(\mu_i, \sigma)$ $Y_j \sim N(\mu_j, \sigma)$ $\Rightarrow Var(Y_i) = Var(Y_j)$	• (paired difference test) • test statistic with *pooled standard deviation* • transformation of Y (Welch's t-test)	existent as the number of pairwise comparisons is $\binom{p}{2}$	Cohen's d, Hedges' g, etc.
One-way ANOVA (F-test)	• $Y_i \overset{i.d.}{\sim} Y_j$ • $Var(Y_i) = Var(Y_j)$ • $\epsilon_i \sim N(0, \sigma^2)$	• (Repeated Measures ANOVA) • transformation of Y (Welch's ANOVA) • incorporation of new factors (ANOVA on ranks)	existent for *post-hoc testing* as the number of pairwise comparisons is $\binom{p}{2}$ not existent in case *contrasts* are being used	η^2
Linear regression (Ordinary least squares) (F-test, t-tests)	• no multi-collinearity between x_i • x_i has a linear influence on y_i • $E(\epsilon_i) = 0 \Leftrightarrow E(y_i) = 0$ • $Cov(\epsilon_i, \epsilon_j) = 0$ • $Var(\epsilon_i) = \sigma^2 = Var(y_i)$ • $\epsilon_i \sim N(0, \sigma^2)$	• using one regressor as a proxy for the others • transformation of y or consideration of *splines* • $\hat{\beta}_0$ usually equalizes this bias • using an *instrumental variable* (Two-stage least-square) • transformation of y or use of (robust regression) techniques • incorporation of new regressors	existent as the number of *dummy variables* equals the number of factor levels	standardized β_i
Two-sample Kolmogorov–Smirnov test	• $Y_i \overset{i.d.}{\sim} Y_j$ • the scale of measurement of Y is at least ordinal		existent as the number of pairwise comparisons is $\binom{p}{2}$	test statistic D
Wilcoxon-Mann-Whitney test Kruskal-Wallis test	• $Y_i \overset{i.d.}{\sim} Y_j$ • $Var(Y_i) = Var(Y_j)$	• (Wilcoxon signed-rank test) • transformation of Y or e.g. (Cliff's method, Brunner-Munzel test)	existent for *post-hoc testing* existent as the number of pairwise comparisons is $\binom{p}{2}$	$r = \frac{Z}{\sqrt{n}}$

Let Y_i and Y_j be two samples of the size n_i, n_j with factor values $X_i = i$, $X_j = j$ and $i, j \in \{1, \ldots, p\}, i \neq j$
Let y_i be the response variable of a linear model with p regressors x_j of the form $y_i = \hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \cdots + \hat{\beta}_p x_{ip} + \epsilon_i, i = 1, \ldots, N$

Brown–Forsythe test on homoscedasticity

Brown and Forsythe (1974) extended the classical test on homoscedasticity suggested by *Levene* in 1960, concluding that a test statistic based on medians instead of means is best at identifying hetroscedasticity particularly for asymmetric distributions (cf. Figure 61 and 62 in B.1).

The test's null hypothesis is the equality of variances of all p factor level group:

$$H_0 : \sigma_1^2 = \sigma_1^2 = \cdots = \sigma_p^2 \tag{3.11}$$

Thus the alternative hypothesis is that the group variances are unequal for at least one group pair:

$$H_1 : \exists i, j \in \{1, \ldots p\} \text{ with } i \neq j \text{ and } \sigma_j^2 \neq \sigma_k^2 \tag{3.12}$$

Let $z_{ij} = |y_{ij} - y_j^{'}|$ be a measure of spread of the ith observation $y_i = \mu_j + \epsilon_{ij}$ with $i = 1, \ldots, n_j$ and unknown population means μ_j and error terms ϵ_{ij} from the median $y_j^{'}$ of the jth group $j = 1, \ldots, p$. Correspondingly, let $\bar{z}_j = \frac{1}{n_j} \sum_{i=1}^{n_j} z_{ij}$ be the the group means of the z_{ij} and $\bar{z} = \frac{1}{n} \sum_{j=1}^{p} \bar{z}_j$ the overall mean of all group means. Together with $n = \sum_{j}^{p} n_j$ the test statistic of the Brown-Forsythe test is:

$$W = \frac{(n-p) \sum_{j=1}^{p} n_j (\bar{z}_j - \bar{z})^2}{(p-1) \sum_{j=1}^{p} \sum_{i=1}^{n_j} (z_{ij} - \bar{z}_j)^2} \overset{d.a.}{\sim} F(p-1, n-p) \tag{3.13}$$

If the ϵ_{ij} are independent and similarly distributed with zero mean and possibly unequal variances the test statistic is asymptotically F-distributed with $p-1$ and $n-p$ degrees of freedoms (Brown and Forsythe, 1974, p. 364).

Cliff's method for two independent groups

Cliff's method is a robust improvement of the Wilcoxon-Mann-Whitney test and seems to perform relatively well under heteroscedasticity based on recent simulation studies. In contrast to other proposed robust alternatives by Reiczigel, Zakariás and Rózsa or Brunner and Munzel or Mee the method is able to maintain its beneficial properties even in the presence of *tied values* (i.e. the existence of observations with equal Y-values) (Wilcox, 2015, p. 352).

For that matter the following probabilities for the ith observation Y_{i1} of group 1, $i = 1, \ldots, n_1$ and the hth observation Y_{i2} of group 2, $h = 1, \ldots, n_2$ assuming statistical independence upon and within both groups are being introduced (Wilcox, 2015, p. 352; Wilcox, 2012, p. 180):

$$\begin{aligned} p_1 &= P(Y_{i1} > Y_{i2}) \\ p_2 &= P(Y_{i1} = Y_{i2}) \\ p_3 &= P(Y_{i1} < Y_{i2}) \end{aligned} \tag{3.14}$$

Cliff's method relies on testing the following null hypothesis:

$$H_0 : \delta = p_1 - p_3 = 0 \tag{3.15}$$

It can be shown that Equation 3.15 is tantamount to

$$H_0 : P = p_3 + 0.5p_2 = 0.5 \tag{3.16}$$

The parameter δ is related to the test statistic P by $\delta = 1 - 2P$. Additionally, Equation 3.16 is in fact the definition of a *stochastic superiority* of variable X_1 over a variable X_2, which leads Vargha and Delaney (1998, p. 176ff) to the finding that the Kruskal-Wallis test is a test on *stochastic homogeneity* (i.e. the equality of rank mean expected values) if the assumption of homoscedasticity is not met. Similarly, Cliff's method is a test on *stochastic superiority*.

Note that an important advantage of Cliff's method is that the parameter δ can be directly interpreted as an *measure of effect size* since it is dimensionless, independent of the measuring unit as well as the sample size of the underlying data and close to zero if H_0 can not be rejected. Compare Cohen (1988) for the classic definition of an effect size.

For the ith observation in group 1 and the hth observation in group 2, let

$$d_{ih} = \begin{cases} -1 & \text{if } Y_{i1} < Y_{h2} \\ 0 & \text{if } Y_{i1} = Y_{h2} \\ 1 & \text{if } Y_{i1} > Y_{h2} \end{cases} \tag{3.17}$$

The test statistic estimate for Cliff's δ then denotes the difference of values being higher in one group than in the other and values being lower in one group than in the other.

$$\hat{\delta} = \frac{1}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{h=1}^{n_2} d_{ih} \tag{3.18}$$

A consistent estimate for the variance $\hat{\sigma}^2$ of $\hat{\delta}$ is given by (Cliff, 1996, p. 139; Wilcox, 2015, p. 354):

$$\begin{aligned} \bar{d}_{i+} &= \frac{1}{n_2} \sum_h d_{ih} \\ \bar{d}_{+h} &= \frac{1}{n_1} \sum_i d_{ih} \\ s_1^2 &= \frac{1}{n_1 - 1} \sum_{i=1}^{n_1} (\bar{d}_{i+} - \hat{\delta})^2 \\ s_2^2 &= \frac{1}{n_2 - 1} \sum_{h=1}^{n_2} (\bar{d}_{+h} - \hat{\delta})^2 \\ \widetilde{\sigma}^2 &= \frac{1}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{h=1}^{n_2} (d_{ih} - \hat{\delta})^2 \end{aligned} \tag{3.19}$$

$$\hat{\sigma}^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2 + \widetilde{\sigma}^2}{n_1 n_2} \tag{3.20}$$

From that a $1 - \alpha$ confidence interval (CI) can be derived either for δ or P (Cliff, 1996, p. 140):

$$C_l = \frac{\hat{\delta} - \hat{\delta}^3 - z\hat{\sigma}\sqrt{(1 - \hat{\sigma}^2 + z^2\hat{\sigma}^2}}{1 - \hat{\sigma}^2 + z^2\hat{\sigma}^2} \tag{3.21}$$

$$C_u = \frac{\hat{\delta} - \hat{\delta}^3 + z\hat{\sigma}\sqrt{(1 - \hat{\sigma}^2 + z^2\hat{\sigma}^2}}{1 - \hat{\sigma}^2 + z^2\hat{\sigma}^2} \tag{3.22}$$

$$z = \Phi^{-1}\left(\frac{1 - \alpha}{2}\right) \tag{3.23}$$

$$CI_{\delta}^{1-\alpha} = [C_l, C_u] \tag{3.24}$$

$$CI_P^{1-\alpha} = \left[\frac{1-C_u}{2}, \frac{1-C_l}{2}\right] \tag{3.25}$$

If the confidence interval for δ does not contain zero, $H_0 : \delta = 0$ is rejected, which means that $H_0 : P = 0.5$ is rejected as well.

In the 'WRS' (Wilcox' Robust Statistics) package used for the implementation in R (R Core Team, 2017) in this work the *p-value* for Cliff's method is calculated iteratively by determining the minimum value of α for which either $C_l > 0$ or $C_u < 0$. This is equivalent to $0 \notin CI_\delta^{1-\alpha}$ and therefore to rejecting the null hypothesis.

Findings of Vargha and Delany from 2002 of a simulation study for small sample sizes ($n \leq 20$) showed that Cliff's method performed better in case the group sample sizes differed compared to other robust ordinal tests, e.g. the *Brunner-Munzel test*. However, serious inflation of type I error still occurred in case very skewed and heavy-tailed distributions and very strong differences in group sample sizes ($> 1 : 2$) were present. In 2003 and 2005 Wilcox showed that Cliff's method performed in general better when data with tied values was used (Neuhäuser et al., 2007, p. 5059). The simulation study from Neuhäuser ($n \leq 20$) confirms the results from Vargha and Delany so that Wilcox concludes that Cliff's method "has a bit of an advantage to control the probability of a type I error" compared to the *Brunner-Munzel test* (Wilcox, 2012, p. 184).

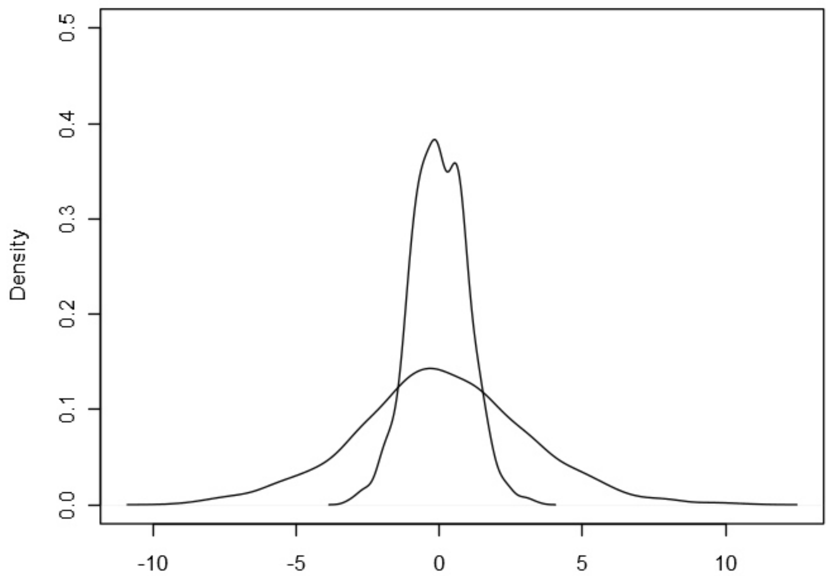


Figure 6: Distributional situation where Cliff's δ is close to zero

An important limitation of Cliff's method is that although $\hat{\delta}$ provides beneficial properties in terms of robustness and power for a variety of skewed and heavy-tailed distributional situations as described above, this comes with the drawback that it is not possible to detect effects apart from those related to differences in central tendency (i.e. a central or typical value for a probability distribution). For example, Figure 6 shows a distributional situation where $\hat{\delta}$ is close to zero even though the distributions of the two groups clearly deviate from each other.

In summary, one has to keep in mind that *p-values* and *confidence intervals* resulting from Cliff's method are fully trustworthy as long as the smallest group sample size is larger than 10 and the group sample size proportion is $\leq 2:1$. Otherwise results should be critically examined. Concerning the conducted analysis in this work especially a mix of reduced sample size (still ≥ 100) and very unequal group sample sizes proportions (>> 2:1) for particular cases lead to ambiguous test results, which will be referred to in Section 3.3. Additionally, effects detected by Cliff's method and evaluated by $CI_{\delta}^{1-\alpha}$ only result from differences in central tendency so that any effects solely resulting from different group variances remain undetected. After all this is a necessary handicap in order to cope with the heteroscedastic, very skew and to some extend heavy-tailed data at hand (cf. Figure 59–62 in B.1).

Controlling the family-wise error rate

Table 8 introduced the *multiple comparisons problem* which occurs when a set of multiple statistical hypotheses are considered simultaneously. If not controlled, testing multiple comparisons leads to an inflation of the overall type I error of the analysis, which substantially lowers the specificity of the conducted analysis. The probability of making such false discoveries is called the *family-wise error rate* (FWER).
Throughout this work a simple-to-implement controlling procedure, namely *Holm-Bonferroni method*, was used to adjust p-values from test results locally (i.e. with respect to all pairwise comparisons of one hypothesized effect on a dependent variable) keeping the *local* α-level at its nominal value, which is denoted by $p_{adj.}$.

Let $T_1, T_2, \ldots, T_k$ be the test statistics of k different tests and $\hat{\alpha}_l(t)$ the critical value of the lth test statistic's outcome $t, l = 1, \ldots, k$ at a predefined global α-level. The classical

Bonferroni method simply compares all $\hat{\alpha}_l(t)$ to $\frac{\alpha}{k}$ in order to control the FWER. As this procedure lowers each α for every tested hypothesis substantially, which reduces the statistical power to correctly identify an effect this method is regarded to be very *conservative*. Holm (1978) proposed a procedure that sequentially compares $\hat{\alpha}_l(t)$ to increasing α levels in an ascending order. For that matter let $\hat{\alpha}_{(1)}, \hat{\alpha}_{(2)}, \ldots, \hat{\alpha}_{(k)}$ be the ordered critical values for the analogously ordered hypotheses $H_{(1)}, H_{(2)}, \ldots, H_{(k)}$:

1. Compare: $\hat{\alpha}_{(1)} \leq \frac{\alpha}{k}$
   - If true: accept $H_{(1)}, H_{(2)}, \ldots, H_{(k)}$ and stop
   - If false: reject $H_{(1)}$ and proceed with step 2
2. Compare: $\hat{\alpha}_{(2)} \leq \frac{\alpha}{k-1}$
   - If true: accept $H_{(2)}, \ldots, H_{(k)}$ and stop
   - If false: reject $H_{(2)}$ and proceed with step 3
3. $\cdots$
4. Compare: $\hat{\alpha}_{(k)} \leq \frac{\alpha}{1}$
   - If true: accept $H_{(k)}$ and stop
   - If false: reject $H_{(k)}$ and stop

In contrast to the classical Bonferroni method this procedure allows higher α-levels for hypotheses with higher critical α-levels providing an increase in statistical power while still maintaining to keep the overall α-level at its nominal level.

Multiple other even less conservative methods to cope with multiple comparison problems exist such as the *Benjamini-Hochberg-Procedure* which controls the *false discovery rate*, i.e. the proportion of false discoveries among all discoveries (Benjamini and Hochberg, 1995). More recent approaches concentrate on Bayesian inference to represent all research questions as parameters in one coherent multilevel model (cf. hierarchical modeling). In a nutshell Gelman et al. (2008) state on the approach: "rather than correcting for a perceived problem, we just build the right model from the start". A more detailed introduction and comparison of different techniques to handle multiple comparison problems is beyond the scope of this work. For further information the interested reader can consult Dickhaus (2014).

3.3 Results and discussion

In order to give an answer to the first research question (cf. Chapter 1) and provide socioeconomically and socio-demographically differentiated information on driving behavior in Germany for the subsequent modeling in Chapter 4, relations between selected dependent variables and specific influencing factors were hypothesized. For that matter specified research questions were defined that describe these relations in an ordinal way (cf. Section 3.2.2) based on empirical findings on mobility patterns of private households in Germany. From that, corresponding testable hypotheses for Cliff's method and the χ^2-test on independence were derived and listed in A.3. Several questions and hypotheses were defined from own reasoning as findings from literature concerning behavioral driving patterns in Germany were limited to rather generic statements given in the final reports of three major mobility studies introduced in Section 2.4 and compared in Section 3.1.2. Attention was paid to define the hypotheses prior to exploratory analysis and statistical testing of the data at hand (De Groot, 2014, p. 193).

This section is firstly structured by the three units of observation used throughout this work: households, vehicles and trips (cf. Table 4, 6 and 7 in Section 3.1.4). Secondly, *main effects* (i.e. the effect of a factor on a dependent variable averaging across the levels of any other factor) and some selected *interaction effects* (i.e. the effect of a factor on a dependent variable dependent on the level of another factor) are presented for every unit of observation. A detailed discussion of all analyzed interaction effects would be beyond the scope of this work, but corresponding test tables and mosaic plots are provided in the appendix for further analysis. Due to large sample sizes of the numerically dependent variables TL-N2, TL-N4, TL-N6, TL-N8 and computational limitations of the 'WRS' (Wilcox' Robust Statistics) R package the analysis of their main effects had to be replaced by a sole analysis of interaction effects controlling for the levels of the factor 'place of residence' (or more precisely the agglomerations: rural, urban , city) in this case.

Highlighting the importance of interaction effects, here a very striking type of interaction effect is introduced called the *Simpson's paradox*. This paradox leads to an ambiguous situation where the analysis of main effects results in an opposite association of the factors than the analysis of their interaction effects would suggest. Similarly, situation exist where there is no main effect present while the analysis of interaction effects suggests an effect though. Typically, these situations point to missing or unobserved causal relations.

Note that the variable nomenclature from Section 3.1.4 is extended towards the specified research questions. For that matter a second hyphen separates the variable coding from a counter for the specified research questions and corresponding testable hypotheses. 'VL-C3-1' would therefore specify the first research questions related to the third categorically dependent variable of interest on the level of vehicles.

In order to enhance the interpretation of the test tables resulting from Cliff's method (cf. A.4) summarizing overviews were generated. An example overview is described by means of Figure 7: The overview shows the influence of three different factors (see labels on the left side of the figure) on the dependent variable Y. Each factor has a specific number of factor levels (rectangles) which each form a group of observations. The rectangle's position on the x-axis denotes the relative tendency that the observations in the group have higher/lower values for Y compared to all other factor levels left/right of the factor level of interest. Note that that the position of a factor level has only relative informative value compared to the other factor levels of the same row and can therefore not be related to the levels of other factors. For further information on the ordinal effect characterization, recapitulate the null hypothesis of Cliff's method (cf. Section 3.2.2). The factor label position on the y-axis denotes the largest pairwise effect size calculated which is always the pairwise effect size of the leftmost and rightmost rectangle in the same row. In case there was not enough horizontal space for aligning all rectangles side by side so that some of them are stacked (or offset to the side due to grouping) the corresponding ambiguous leftmost or rightmost factor labels are denoted with a star (*).
For that matter let $||\bar{\delta}||_\infty = max(\bar{\delta})$ be the maximum norm of all $\binom{p}{2} = |\{1, \ldots, k\}|$ absolute estimated confidence intervals (CI) means for Cliff's δ with p number of factor levels and

$$\bar{\delta} = (\overline{|CI|}^{1-\alpha}_{\delta_1}, \ldots, \overline{|CI|}^{1-\alpha}_{\delta_k}) \tag{3.26}$$

For example, the pairwise effect size of 'level 1' and 'level 3' of 'factor 1' is 0.99 which indicates a very large tendency that observations from group three have higher values for Y than from group one. As this effect size is close to the maximum of one, the factor is positioned above all other factors with lower maximum pairwise effect sizes.

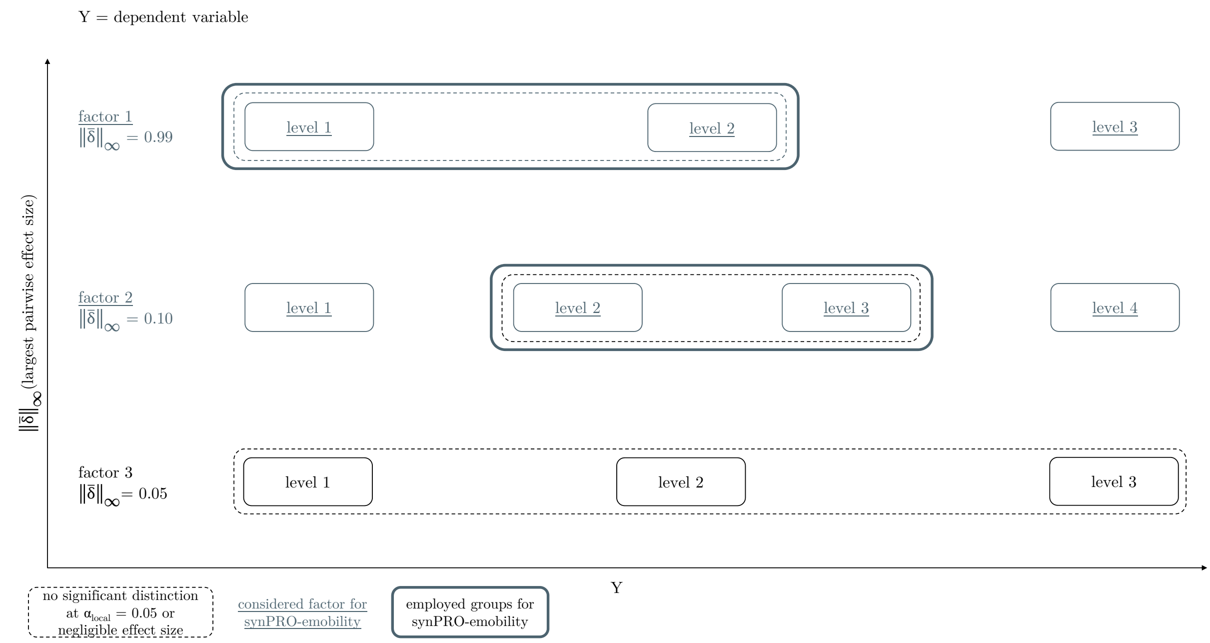


Figure 7: Exemplary overview of interpreted results from test tables of Cliff's method

Dotted rectangles encircling several factor levels indicate that there was no significant pairwise distinction of all involved factor levels at a local α-value of 0.05 or the effect sizes were 'negligible'.

$$\begin{aligned} \text{negligible: } 0.0 \leq \overline{|CI|}_\delta^{1-\alpha} &< 0.1 \\ \text{small: } 0.1 \leq \overline{|CI|}_\delta^{1-\alpha} &< 0.3 \\ \text{medium: } 0.3 \leq \overline{|CI|}_\delta^{1-\alpha} &< 0.5 \\ \text{large: } 0.5 \leq \overline{|CI|}_\delta^{1-\alpha} &\leq 1 \end{aligned} \tag{3.27}$$

The effect size categories for standardized effect size measures used throughout this work were adopted from Cohen (1988) which are widely spread and acknowledged. Recently proposed lower effect size categories from Gignac and Szodorai (2016) were not applicable for the data at hand since they resulted in a majority of 'large' effects for Cohen's 'small' and 'medium' effect categories which made a differentiation difficult. Cohen's categories were also used for the classification of Cramer's V:

$$\begin{aligned} \text{negligible: } 0.0 \leq V &< 0.1 \\ \text{small: } 0.1 \leq V &< 0.3 \\ \text{medium: } 0.3 \leq V &< 0.5 \\ \text{large: } 0.5 \leq V &\leq 1 \end{aligned} \tag{3.28}$$

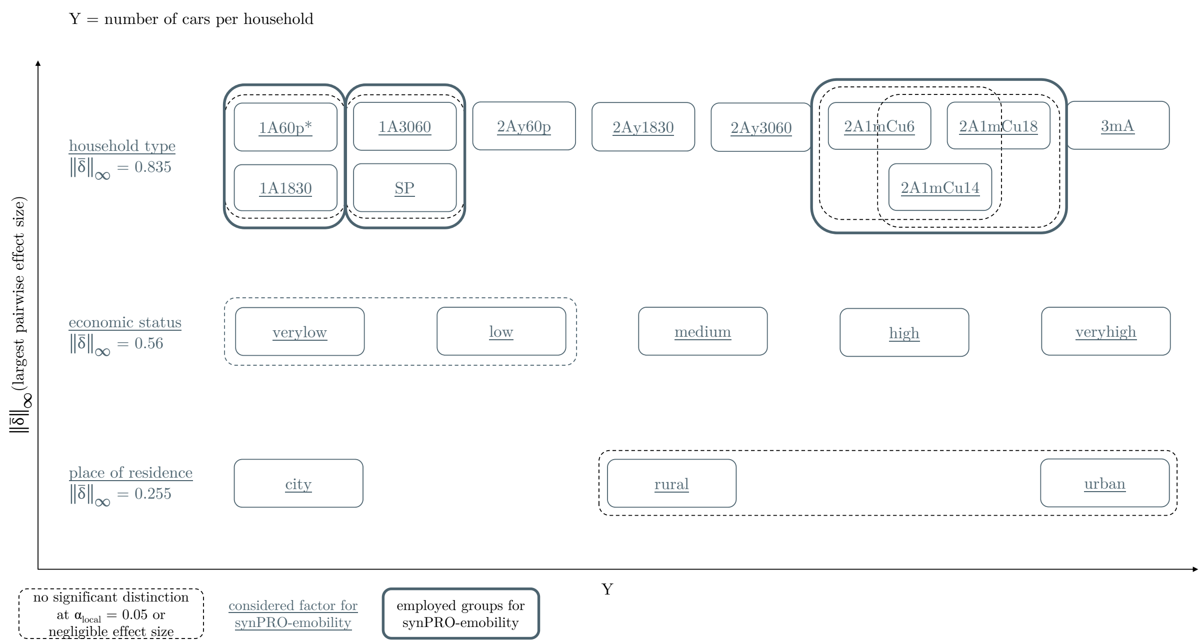
Factor labels underlined and greenish colored indicate that they were considered for the modeling of synPRO-emobility (cf. Chapter 4). In general only ‘small’, ‘medium’ and ‘large’ effects were considered for that matter. Therefore ‘factor 3’ in Figure 7 is not underlined as its largest pairwise effect size is $0.05 < 0.1$.

Factor levels encircled with a greenish colored rectangle indicate employed groups of factor levels. This accounts only for factors that are considered in synPRO-emobility and groups of factor levels whose effects are mutually insignificant or negligible (as long as group sample sizes allowed a fully mutually exclusive modeling). For that reason ‘level 1’ and ‘level 2’ of ‘factor 1’ as well as ‘level 2’ and ‘level 3’ of ‘factor 2’ in Figure 7 are highlighted as described above.

This proceeding helps to maintain reasonable sample sizes for single factor levels or within factor level groups, granting a better representativeness of the generated information used as model input in Section 4. Simultaneously, it allows for considering a larger number of influencing factors with non-negligible effect sizes. Moreover, the approach underpins the general idea of scientific modeling: to abstract from reality and consider ideally the strongest and least data-consuming effects with causal relation to the modeling purpose of interest.

3.3.1 Household level

For a representation of households' driving behavior in Germany at the system level it is necessary to determine the number of available BEV for a specific number of households e.g. in a quarter, city or whole region given a specific BEV market penetration rate. Similarly to the general assumption made in terms of driving behavior (cf. Chapter 3.1.1), here it is assumed that the purchasing decision of households for EV won't alter from that of ICEV. For reasons of simplification it is also assumed that BEV market penetration is equal amongst households. For further information on the sampling procedure of the number of BEV using a BEV market penetration rate, see Section 4.1.3.
For the matter of socio-economic and sociodemographic differentiation the following specified research questions and corresponding testable hypotheses (cf. A.3.1) are proposed to analyze effects on the number of available cars per household.



For a description of factor levels, see A.1.2.

FIGURE 8: HOUSEHOLD LEVEL: OVERVIEW OF MAIN EFFECTS ON NUMBER OF CARS PER HOUSEHOLD (CF. TABLE 18)

HL-N1-1: Do households with higher incomes tend to have more cars available in comparison to households with lower incomes?

Results in Figure 8 show that the most influential main effect on the number of cars available in a German household is the household type, followed by the economic status and the place of residence. The null hypothesis of research question HL-N1-1 can be rejected at

$\alpha_{local} = 0.05$ since a higher income is clearly associated with the tendency to have more cars available in a household compared to a household with lower incomes. However, there is no significant distinction between the factor level groups 'very low' and 'low' at $\alpha_{local} = 0.05$.

HL-N1-2: Do family households tend to have more cars available in comparison to non-family households?

The order of levels for the factor 'household type' shows that an increasing number of adult household members is associated with the probability of having more cars available in a household. Additionally, age seems to play a role as households with a youngest adult household member between 30 and 60 years have a tendency to have more cars available both for single person and two-person households compared to households with a youngest adult household member under 30 or above 60 years. Households with minimum one child under 18 years (family households) distinguish from two-person (as well as from single person and single parent) households significantly, having a clear tendency for more cars available in the household. As households with minimum three adult household members are not necessarily family households, and single parent households clearly distinguish from the other family households, the null hypothesis of research question HL-N1-2 can not be rejected at $\alpha_{local} = 0.05$. A more differentiated null hypotheses for family households with a minimum of one child under or above 18 years excluding single parents households might be rejected though.

HL-N1-3: Do households from rural areas tend to have more cars available than households from urban or city areas?

Concerning the factor 'place of residence' the largest pairwise effect size is relatively small showing a significant distinction of 'city' households compared to 'rural' households at $\alpha_{local} = 0.05$. The null hypothesis of HL-N1-3 can therefore be rejected. However, there is no significant distinction between 'rural' and 'urban' households at $\alpha_{local} = 0.05$.
Due to the relatively small value of $||\bar{\delta}||_\infty$ one might hypothesize that the there is actually no significant distinction of city households compared to households in rural or urban areas and the observed main effect may result from an interaction effect of the involved factors. For example, it could be in general more likely that family households live in rural

or urban areas and are therefore primarily responsible for the main effect between city and non-city households (cf. Figure 9).

HL-C2-1: Is the household's type dependent on the household's place of residence?

Figure 9 shows that the factor 'household type' is in general statistically dependent on the factor 'place of residence' based on a χ^2-test of independence at $\alpha_{local} = 0.05$. The null hypothesis of HL-C2-1 can therefore be rejected. The overall association between these factors is barely 'small' based on Cramer's V and Cohen's effect size categories. Examining where the dependency originates from using the mosaic plot, one can see that it is for example more likely that family households ('2A1mCu6', '2A1mCu14', '2A1mCu18') tend to exist in 'rural' or 'urban' areas (respectively blue shaded tiles in row 2 and 3) than in 'cities' (respectively red shaded tiles in row 1) since the width of the tiles (i.e. the conditional probability of observing a specific value in the corresponding contingency table given a specific factor level of the independent variable) differs noticeably even though not very strongly.

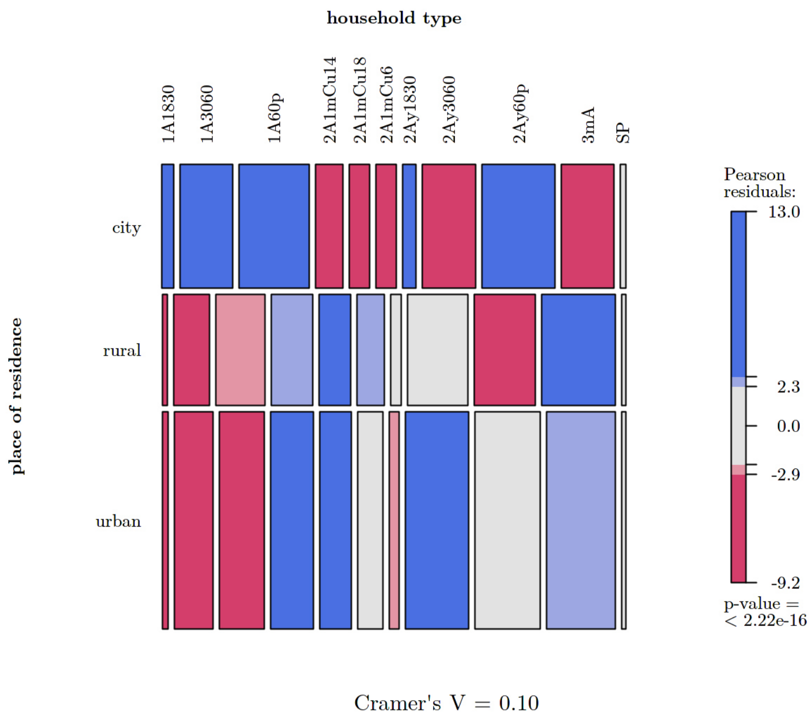


FIGURE 9: HOUSEHOLD LEVEL (χ^2-TEST AND MOSAIC PLOT): MAIN EFFECT OF PLACE OF RESIDENCE ON HOUSEHOLD TYPE

Tables 26, 27 and 28 in A.4.1 show however that the significant distinction at $\alpha_{local} = 0.05$ (together with a small effect size) of 'city' households compared to households from 'urban' or ‘rural’ areas concerning the number of cars available in a household is still present when controlling for the respective household types (cf. ‘combined household type’ with factor levels ‘2A1mCu6-18+SP’ and ‘1-3A’). Therefore one can conclude that the supposed interaction effect of family households in rural or urban areas is not present. However, this result does not imply that there might be other interaction effects present in the data.

In general, all tested interaction effects concerning the number of cars available in a household are consistent with the identified main effects presented above (cf. Table 19 to 37 in A.4.1). However, some significant distinctions at $\alpha_{local} = 0.05$ become insignificant when being controlled for other factor levels (cf. ‘high vs. very high’ in Table 26). This is most likely due to decreasing statistical power along with decreasing sample sizes.

More detailed reasoning on interaction effects is left to the interested reader. For that matter information on for possible additional interaction effects are presented in A.5.1.

3.3.2 Vehicle level

An important dependent variable for households' driving behavior is the *number of trips* driven on a *use day*. A use day is thereby defined as a day on which the households' car is used by its *primary driver* (also referred to as *main user* throughout this work). Further information on the analysis of use or disuse days will be given later in this section. Here, it is first assumed that the analysis of the primary drivers' attributes sufficiently describes the driving behavior of the corresponding reported car of the household, neglecting all deviating attributes of other household members that may have used the same car on the households' survey due day. In order to justify the analysis of primary drivers Figure 10 shows the distribution of driven trips over the number of distinct households' drivers per car on each household's survey due day. One can see that a large majority of trips (84 %) were driven by only one driver indicating that a reported main user of a single car might in fact declare the largest proportion of information on driving behavior on the vehicle level.

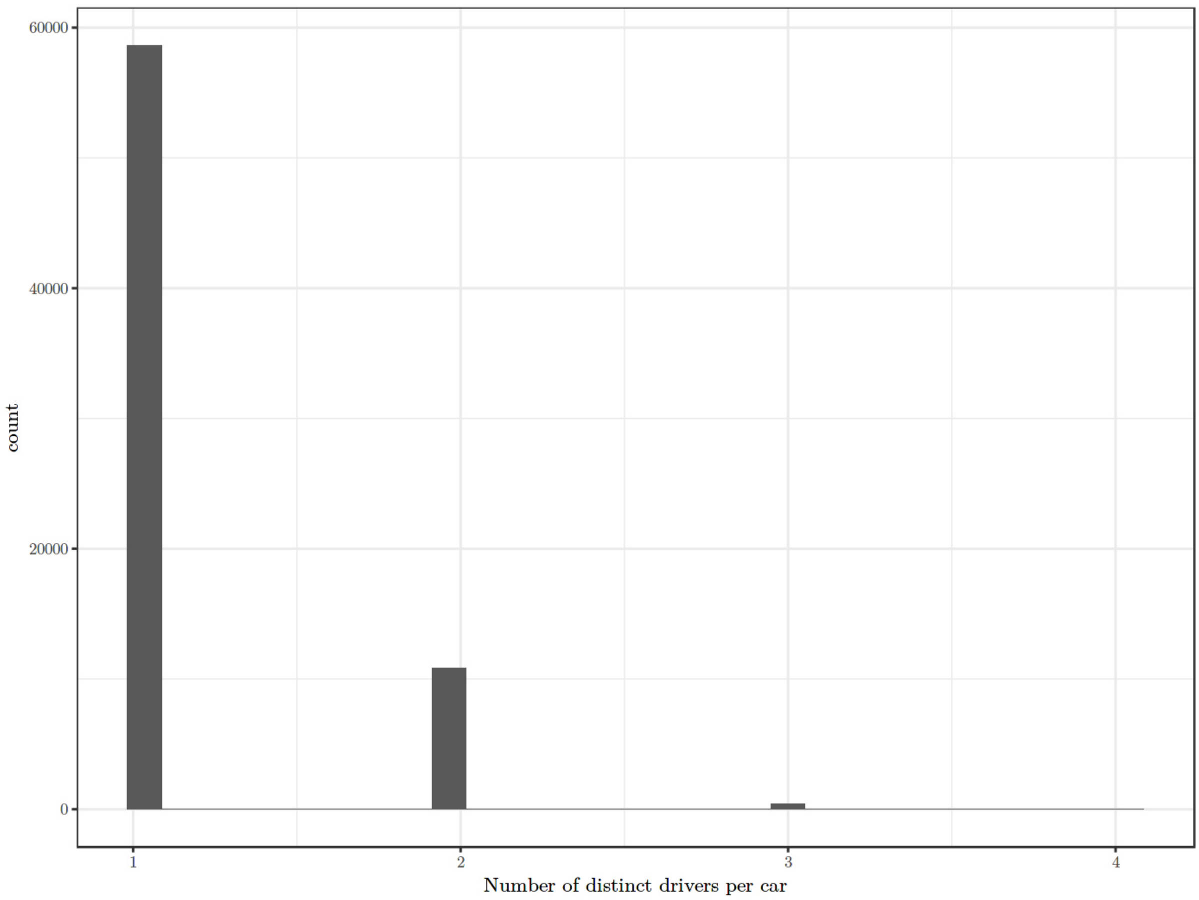


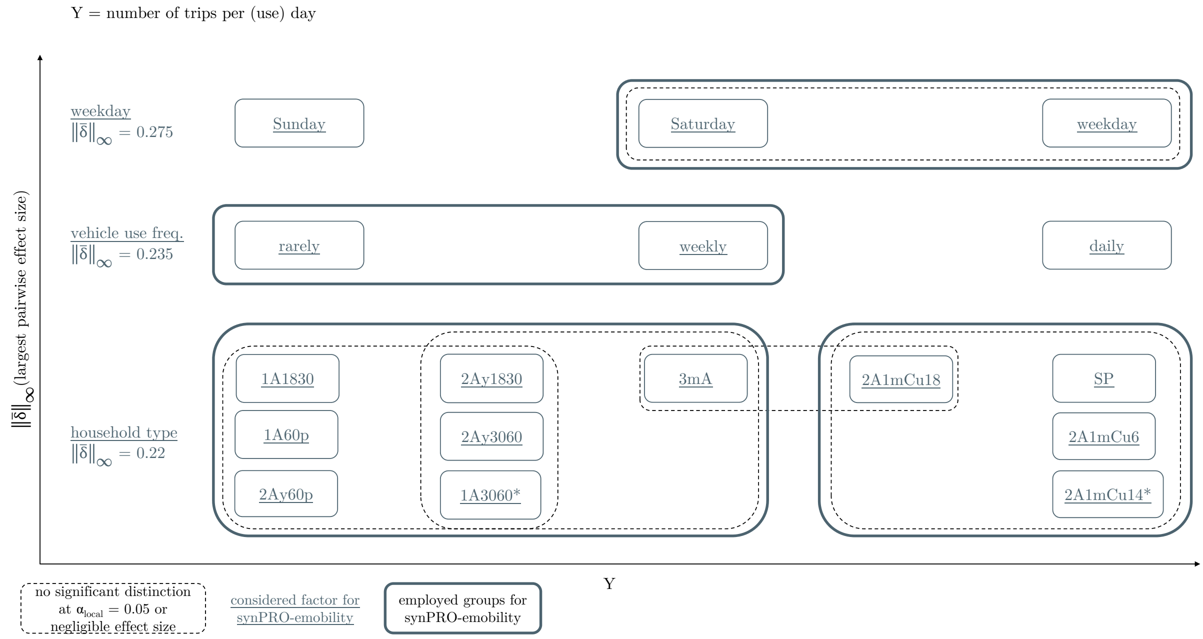
FIGURE 10: HISTOGRAM OF DRIVEN TRIPS DISTRIBUTED OVER THE NUMBER OF DISTINCT DRIVERS PER HOUSEHOLD AND CAR

In reference to a socio-economical and sociodemographic differentiation the following specified research questions and corresponding testable hypotheses are proposed to analyze effects on number of trips per (use) day:

VL-N1-1: Do primary drivers from households with a higher economic status tend to drive more trips per day in comparison to primary drivers from households with lower economic status?

VL-N1-2: Do primary drivers from family households tend to drive more trips per day in comparison to primary drivers from non-family households?

VL-N1-3: Do primary drivers from rural households tend to drive more trips per day in comparison to primary drivers from households from urban or city areas?



For a description of factor levels, see A.1.2.

Figure 11: Vehicle level: overview of main effects on number of trips per (use) day (cf. Table 38 and 39) (I)

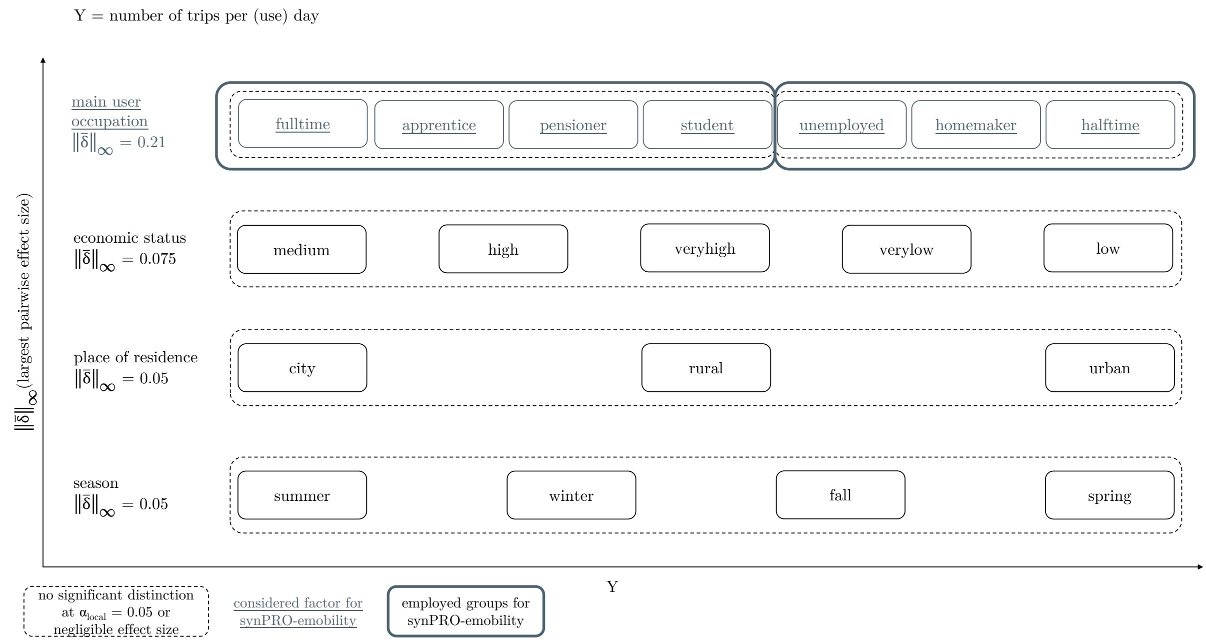
VL-N1-4: Do primary drivers occupied as homemakers tend to drive more trips per day in comparison to primary drivers otherwise occupied?

VL-N1-5: Do primary drivers with a higher vehicle use frequency tend to drive more trips per day in comparison to primary drivers with a lower vehicle use frequency?

VL-N1-6: Do primary drivers tend to drive more trips per day in wintertime than in the other seasons?

VL-N1-7: Do primary drivers tend to drive more trips per day on workdays than on the other days of the week?

Figure 11 and 12 show that the factor 'weekday' has the strongest largest pairwise effect on the number of trips per (use) day upon all hypothesized influencing factors followed by the factor 'vehicle use frequency', 'household type' and 'main user occupation'. All four considered factors have only a 'small' $||\bar{\delta}||_{\infty}$. The factors 'economic status', 'place of residence' and 'season' only had a negligible largest pairwise effect size or were not significant at $\alpha_{local} = 0.05$. Hence, the null hypotheses for VL-N1-1, VL-N1-3 and VL-N1-6 cannot be rejected.



For a description of factor levels, see A.1.2.

FIGURE 12: VEHICLE LEVEL: OVERVIEW OF MAIN EFFECTS ON NUMBER OF TRIPS PER (USE) DAY (CF. TABLE 38 AND 39) (II)

The order of factor levels for the factor 'weekday' shows a strong tendency that a higher number of trips are driven on workdays or Saturdays than on Sundays. Therefore the null hypothesis VL-N1-7 can be rejected at $\alpha_{local} = 0.05$. However, there was no significant distinction between the factor levels 'Saturday' and 'workday'. The result might be explained by the presumption that many usual trips on workdays are replaced with leisure or shopping trips on Saturdays whereas Sundays are rather spent at home.

Concerning the factor 'vehicle use frequency' there was a clear significant distinction between all factor levels. One can see that primary drivers who reported a more frequent car use (in terms of time units beyond days) also tend to drive more trips per (use) day. VL-N1-5 can therefore be rejected at $\alpha_{local} = 0.05$ based on the finding of this main effect. The factor levels 'rarely' and 'weekly' had to be grouped since the sample size of the factor level 'rarely' was only 165 cars which was too little in combination with all other employed factor level groups for the subsequent modeling in Chapter 4.

The factor level order for the factor 'household type' clearly shows a tendency that primary drivers from family households cover more trips per (use) day than primary drivers from non-family households. The null hypothesis VL-N1-2 can therefore be rejected at $\alpha_{local} = 0.05$. This result can be explained by the presumption that parents usually have higher mobility commitments due to the mobility needs of their children.

Regarding the factor 'main user occupation', two significant factor level groups are present. One group consisting of primary drivers occupied 'fulltime' or as 'apprentice', 'pensioner' or 'student' tends to drive fewer trips per (use) day. The other group consisting of 'unemployed', 'homemaker' or 'halftime' occupied primary drivers tends to drive more trips per (use) day. Accordingly, the null hypothesis for research question VL-N1-4 can not be rejected at $\alpha_{local} = 0.05$. However, it could be rejected when grouping the factor levels 'homemaker', 'unemployed' and 'halftime'.

At this point one might hypothesize that there is a main effect present between the factors 'household type' and 'main user occupation' resulting in an interaction effect for the number of trips per (use) day. For example, primary drivers who are 'halftime' occupied or occupied as 'homemakers' could be generally associated with family households so that this main effect actually may result from the main effect of family households.

Figure 13 shows that the statistical dependence for both factors is clearly significant based on a χ^2-test of independence at $\alpha_{local} = 0.05$. The null hypothesis of VL-C1-1 can therefore be rejected. Cramer's V indicates that the general association between the factors is 'medium', also indicated by the strong varying tile widths of the mosaic plot. From that, one can see that the main user occupations 'halftime' and 'homemaker' (fourth and third tile counting from the right) are fore example more likely to occur in family households (row 4, 5, 6 and 11 counting from above).

VL-C1-1: Is the main user's occupation dependent on the main user's household type?

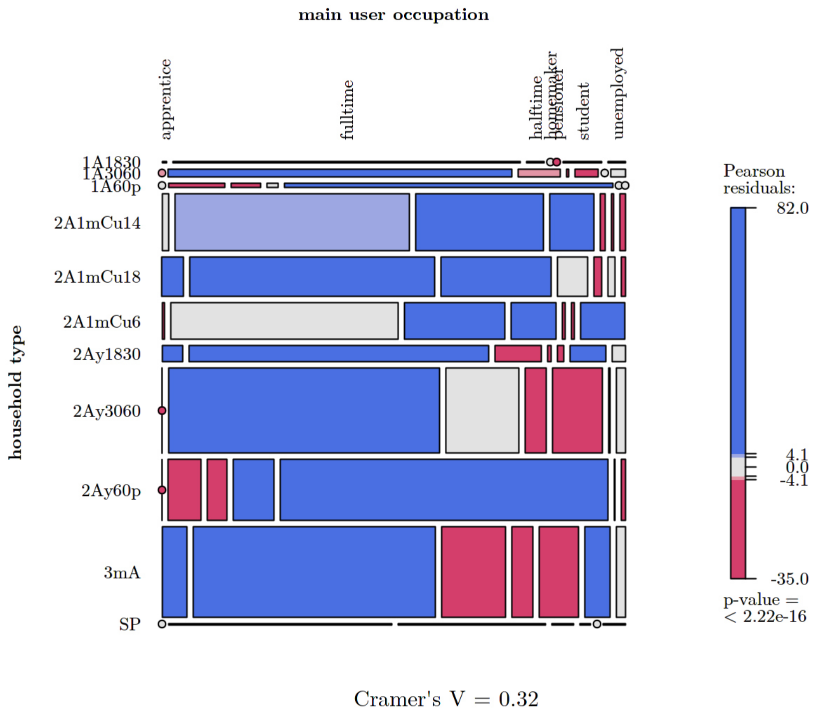


Figure 13: Vehicle level (χ^2-test and mosaic plot): main effect of household type on main user occupation

However, Table 43 in A.4.2 shows that there is still a significant and 'small' sized effect between the factor levels 'fulltime' and the factor levels 'homemaker' or 'halftime' when controlling for all family household types (cf. 'combined household type' with factor levels '2A1mCu6-18+SP' and '1-3A'). This indicates that the hypothesized interaction effect that primary drivers who are occupied 'halftime' or occupied as 'homemakers' is only due to the fact that they are more likely to exist in family households does not hold. However, this does not eliminate in general the presence of other interaction effects since other comparisons, e.g. 'halftime' vs. 'pensioner', are not significant when being controlled for family households. Very unequal and lowered group sample sizes in these cases ($> 1:2$, cf. Section 3.2.2) might be responsible for a drastically decreasing power of the tests applied, so that the original factor level order of the main effect might hold when controlling for family household types but could not be detected by the test.

In general most main effects remain unchanged when looking at interaction effects of the involved factors. However, results on the factor ‘main user occupation’ become insignificant when controlling for Sundays and the factor levels ‘pensioners’ and ‘students’ are no longer significant against any other level of the factor ‘main user occupation’ when being controlled for family or non-family households (cf. Table 38 and 39). More detailed reasoning on interaction effects is left to the interested reader. For that matter information on further possible interaction effects are presented in A.4.2 together with A.5.2.

Having analyzed the main effects present for the number of trips per day it is also necessary to look at effects concerning the categorically dependent variables ‘main user (vehicle) use frequency’ and ‘main user (daily vehicle) use’ (cf. Table 5) describing households’ driving behavior beyond an in-day viewing. Limitations to the informative value of these variables were described before (cf. Section 3.1.3). Here, it is worth noting again, that it is assumed in the context of this analysis that the observed variable values reflect the typical average driving behavior of primary drivers for time horizons such as weeks or months.

VL-C2-1: Is the main user’s (vehicle) use frequency dependent on the main user’s household type?

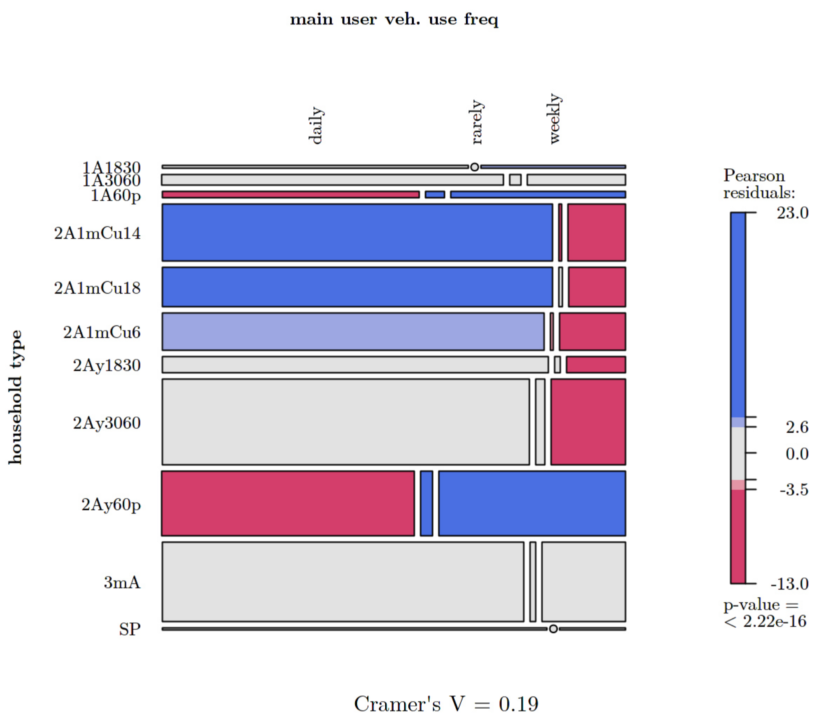


Figure 14: Vehicle level (χ^2-test and mosaic plot): main effect of household type on main user (vehicle) use frequency

Regarding the factor 'main user (vehicle) use frequency', Figure 14 shows a significant statistical dependence on the household type based on a χ^2-test of independence at $\alpha_{local} = 0.05$. Therefore the null hypothesis of VL-C2-1 can be rejected. Based on Cramer's V and Cohen's effect size categories, the general association between the two factors can be described as 'small'. Using the mosaic plot one can determine a clear pattern, that households with minimum one adult over 60 years (cf. width of the leftmost red shaded tile in row 3 and 9) are less likely to use the car more frequently than all other household types. Simultaneously, family households are slightly more likely to use the car more frequently compared to other household types (cf. blue shaded leftmost tile in row 4, 5, 6 and 11).

VL-C2-2: Is the main user's (vehicle) use frequency dependent on the main user's occupation?

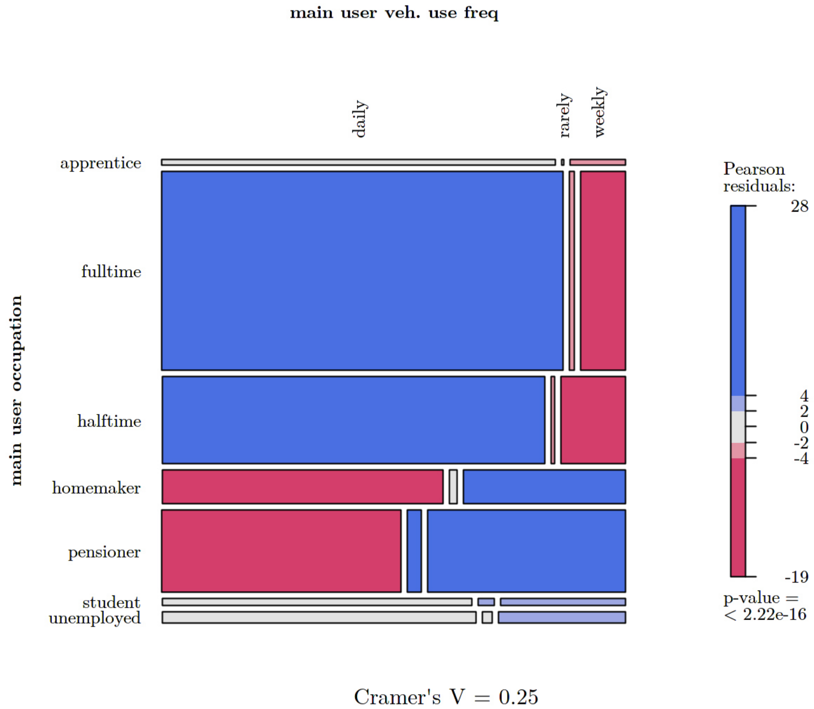


FIGURE 15: VEHICLE LEVEL (χ^2-TEST AND MOSAIC PLOT): MAIN EFFECT OF MAIN USER OCCUPATION ON MAIN USER (VEHICLE) USE FREQUENCY

Another influence on the dependent variable 'main user (vehicle) use frequency' is shown in Figure 15. One can see, that it is significantly dependent on the factor main user occupation based on a χ^2-test of independence at $\alpha_{local} = 0.05$. The null hypothesis for VL-C2-3 can therefore be rejected. Following Cramer's V the association can be described as 'small'. Building on the findings of VL-C1-1 one could hypothesize that homemakers are more likely to use the car more frequently than primary drivers otherwise occupied since they are associated with family households. Looking closer into the dependency structure using the mosaic plot it is striking that primary drivers occupied as homemakers are only more likely to use the car more frequently when being compared to primary drivers occupied as pensioners. Primary drivers who are full-time or halftime working, occupied as apprentice or student or who are unemployed are noticeably more likely to use the car more frequently.

Regarding the influence of the factor ‘place of residence’ on the ‘main user (vehicle) use frequency’ Figure 16 shows a significant statistical dependency based on a χ^2-test of independence at $\alpha_{local} = 0.05$. Cramer’s V indicates a ‘negligible’ association though. Primary drivers from city households seem to be a little bit less likely to use the car on a daily basis. Due to the negligible overall association effect size this influencing factor was not considered fro synPRO-emobility.

VL-C2-3: Is the main user’s (vehicle) use frequency dependent on the main user’s place of residence?

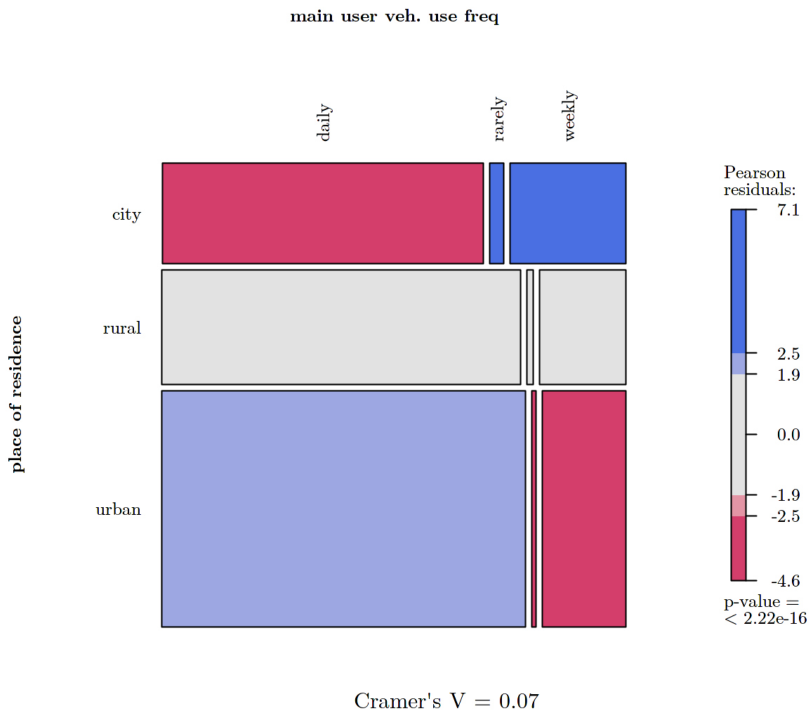


Figure 16: Vehicle level (χ^2-test and mosaic plot): main effect of place of residence on main user (vehicle) use frequency

Next, results on influencing factors on the dependent variable ‘main user (daily vehicle) use’ are presented.

VL-C3-1: Is the main user's (daily vehicle) use dependent on the main user's (vehicle) use frequency?

Figure 17 shows that there is significant statistical dependency between the two dependent variables 'main user (vehicle) use frequency' and 'main user (daily vehicle) use' based on a χ^2-test of independence at $\alpha_{local} = 0.05$. The magnitude of the association can be denoted with 'small' following Cramer's V and Cohen's effect size categories. One can see, that a more frequent vehicle use is also clearly associated with an increasingly higher probability that a primary driver uses the car on a particular day.

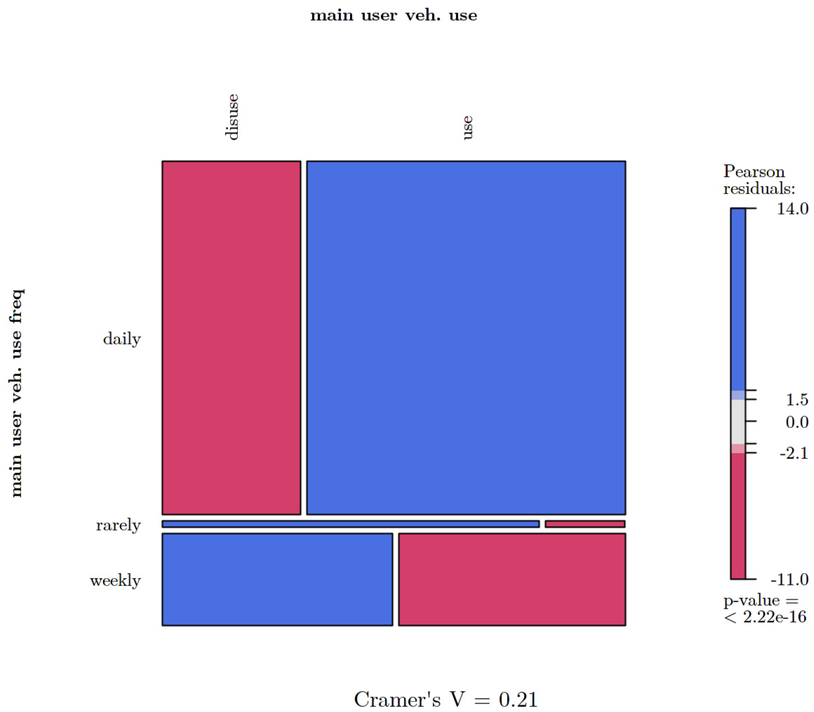
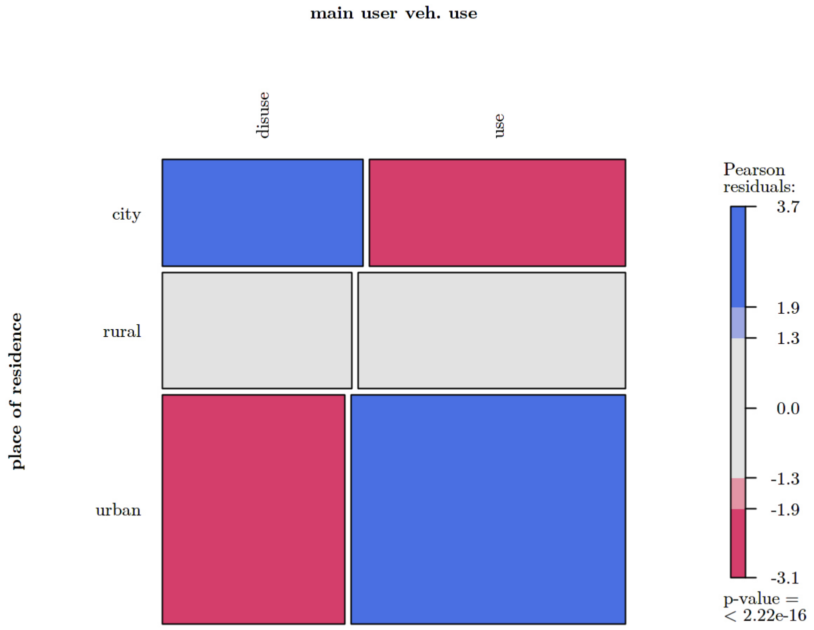


FIGURE 17: VEHICLE LEVEL (χ^2-TEST AND MOSAIC PLOT): MAIN EFFECT OF MAIN USER (VEHICLE) USE FREQUENCY ON MAIN USER (DAILY VEHICLE) USE

VL-C3-2: Is the main user's (daily vehicle) use dependent on the main user's place of residence?

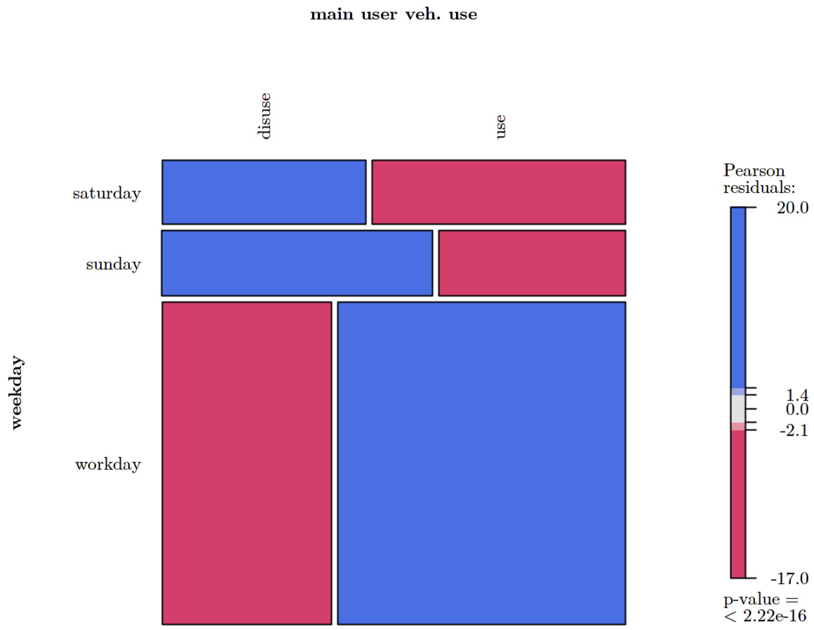
Concerning an influence of the households' place of residence on the 'main user (daily vehicle) use' probability Figure 18 shows a significant statistical dependency based on a χ^2-test of independence at $\alpha_{local} = 0.05$. However, the overall association is 'negligible' since Cramer's V is noticeably below Cohen's threshold of 0.1. Therefore the association between the factor 'place of residence' and the 'main user (daily vehicle) use' is not considered for synPRO-emobility.



Cramer's V = 0.03

FIGURE 18: VEHICLE LEVEL (χ^2-TEST AND MOSAIC PLOT): MAIN EFFECT OF PLACE OF RESIDENCE ON MAIN USER (DAILY VEHICLE) USE

VL-C3-3: Are primary drivers more likely to use the car on workdays compared to Saturdays or Sundays?



Cramer's V = 0.16

FIGURE 19: VEHICLE LEVEL (χ^2-TEST AND MOSAIC PLOT): MAIN EFFECT OF WEEKDAY ON MAIN USER (DAILY VEHICLE) USE

Figure 19 shows that the factor 'weekday' has a 'small' overall effect on the 'main user (daily vehicle) use' and that the dependency is clearly statistically significant. One can see, that it is evidently more likely for primary drivers to use the car on a particular workday than on a Saturday or Sunday. Simultaneously, it is more likely for Saturdays compared to Sundays.

3.3.3 Trip level

On the level of trips four dependent variables describing households' driving behavior were analyzed: *driven distance*, *departure time* (of the first trip per day), *driving time* and *parking time*. The reason for limiting the analysis of the departure time to the first trip of the day is due to the fact that the departure time (as well as the arrival time) of all subsequent trips derive from the information on their driving and parking time. All four variables were analyzed both for trips to the workplace (all) and back (only driven distance and driving time) as well as trips to other destinations inside or outside the primary driver's city or town (cf. 3.1.3). This proceeding allows for a differentiated spatial modeling in Chapter 4.
With respect to a socio-economical and sociodemographic differentiation the following specified research questions and corresponding testable hypotheses are proposed to analyze effects on the driven distance per trip:

TL-N1-1: Do primary drivers who are occupied full-time tend to drive longer distances to work (or from work home) compared to primary drivers who are otherwise occupied?

TL-N1-2: Do primary drivers of rural households tend to drive longer distances to work (or from work home) compared to primary drivers from urban or city households?

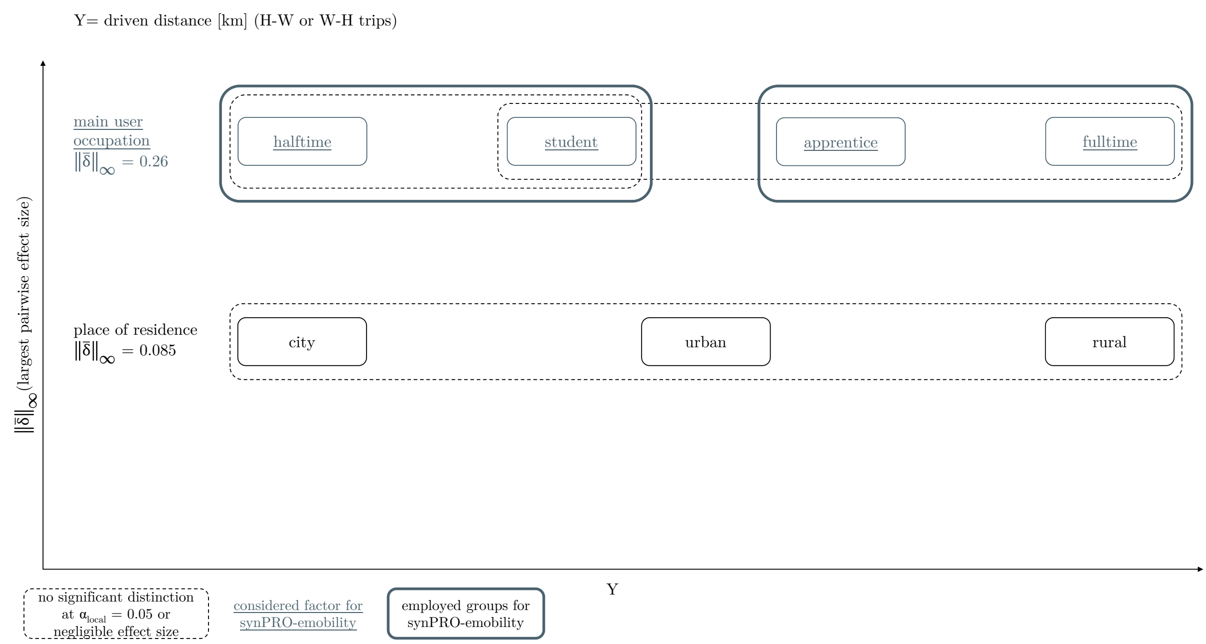


Figure 20: Trip level: overview of main effects on driven distance for H-W or W-H trips (cf. Table 50)

Figure 20 shows that the factor ‘main user occupation’ has the largest pairwise effect size of both hypothesized influencing factors on the driven distance to work or from work back to home. Regarding the factor level order one can see that primary drivers who are ‘fulltime’ occupied does not tend to drive longer distances to work than all other factor levels. The null hypothesis of TL-N1-1 can therefore not be rejected at $\alpha_{local} = 0.05$. In fact the test result is ambiguous as the factor level order shows an situation where there is no significant distinction of the factor level ‘student’ compared to all other factor levels. Simultaneously, there is significant distinction between the factor level ‘halftime’ and two other factor levels ‘apprentice’ and ‘halftime’. Taking a closer look on Table 50 one can see that this test situation is most likely due to drastically decreased power for the pairwise comparisons of ‘halftime vs. student’ and ‘fulltime vs. student’ as the ‘student’ factor level sample size is 106 compared to 3065 (for ‘halftime’) and 10207 (for ‘fulltime’). However, the pairwise comparison ‘apprentice vs. student’ was also insignificant given a better – but still critical – sample size ratio of 339:106 (cf. Section 3.2.2). It was therefore assumed that there is a significant distinction between the factor levels ‘fulltime’ and ‘student’ employing the groups for synPRO-emobility as illustrated in the figure.
For the factor ‘place of residence’ all pairwise comparisons are either insignificant at $\alpha_{local} = 0.05$ or have a negligible effect size. The null hypothesis of TL-N1-2 can therefore not be rejected. As a consequence only the factor ‘main user occupation’ was considered for synPRO-emobility together with two factor level groups as illustrated above.

Concerning the driven distance for all trips except H-W and W-H trips the following five specified research questions were defined:

TL-N2-1: Do leisure trips tend to have a longer driven distance compared to trips with other trip purposes?

TL-N2-2: Do outside city trips tend to have a longer driven distance compared to inside city trips?

TL-N2-3: Do trips driven on a day with multiple other trips tend to have a longer driven distance compared to trips driven on a day with fewer trips per (use) day?

TL-N2-4: Do trips driven on a workday tend to have a shorter driven distance compared to trips driven on a Saturday or Sunday?

TL-N2-5: Do trips driven in wintertime tend to have a longer driven distance compared to trips driven in other seasons?

Figure 21 shows that the added factor ‘trip distance category’ has the largest effect on the driven distance on trips other than H-W or W-H trips. All pairwise comparisons were significant at $\alpha_{local} = 0.05$ and ‘outside city’ trips are evidently more likely to have a longer distance than ‘inside city’ trips and trips of the category ‘unknown’ which comprise primarily of trips from places located inside or outside the primary driver’s own city or town to his workplace. Therefore the null hypothesis of TL-N2-2 can be rejected. The $||\bar{\delta}||_\infty$-value is the largest observed pairwise effect size of all analyzed influencing factors upon different numerically dependent variables regarding the trip level indicating that spatial information in form of the variable ‘departure arrival place’ are very likely to be correctly assigned to all trips (cf. Section 3.1.3).

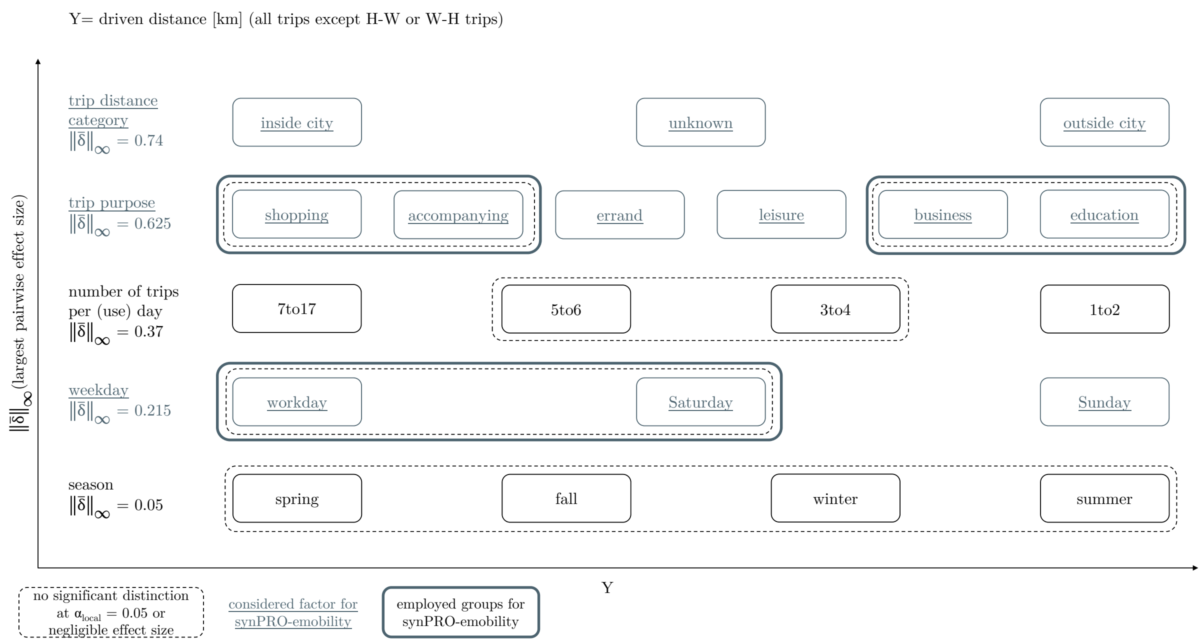


FIGURE 21: TRIP LEVEL: OVERVIEW OF MAIN EFFECTS ON DRIVEN DISTANCE FOR ALL TRIPS EXCEPT H-W OR W-H TRIPS (CF. TABLE 51, 52, 53)

The factor ‘trip purpose’ has the second largest pairwise effect size which can be denoted as ‘large’ based on Cohen’s effect size categories. The factor level order indicates that trips with the trip purpose ‘business’ or ‘education’ (mutually not significant at $\alpha_{local} = 0.05$) tend to be more likely to have a longer driven distance for all trips other than H-W or W-H trips – particularly more likely than ‘leisure’ trips. Therefore the null hypothesis of TL-N2-1 can not be rejected. Trips with the trip purpose ‘shopping’ or ‘accompanying’ (mutually not significant at $\alpha_{local} = 0.05$) are more likely to have the lowest driven distance.

Regarding the factor 'number of trips per (use) day' (cf. VL-N1 in Section 5) one can evidently see that a higher number of trips driven per day is associated with smaller driven distances per trip. Therefore the null hypothesis of TL-N2-3 can be rejected at $\alpha_{local} = 0.05$. This result is consistent with results from exploratory data analysis as Figure 61 in B.1 confirms (cf. scatter plot in the upper right corner and corresponding correlation coefficients in the lower left corner). However, the factor levels '5to6' and '3to4' are not significant at $\alpha_{local} = 0.05$. The largest pairwise effect size can be denoted with medium based on Cohen's categories. The factor was not considered directly (i.e. as a variable) but rather indirectly making use of a rejection approach for the algorithmic implementation of synPRO-emobility (cf. Section 4.2).
Concerning the factor 'weekday' the largest pairwise effect size can be denoted with 'small' based on Cohen's effect size categories. The factor level order indicates that trips driven on workdays or Saturdays (mutually not significant at $\alpha_{local} = 0.05$) tend to have a lower driven distance than trips driven on Sundays. Strictly speaking, the null hypothesis of TL-N2-4 can therefore not be rejected at $\alpha_{local} = 0.05$. However, it could be rejected as stated above.
Surprisingly, all factors levels of the factor season are either insignificant at $\alpha_{local} = 0.05$ or have a 'negligible' effect size. For that matter, the null hypothesis of TL-N2-5 can not be rejected.

Next, four specified research questions and results regarding the departure time of the first trip per day are presented:

TL-N3-1: Do primary drivers who are occupied full-time tend to depart earlier to work on their first trip of the day compared to primary drivers who are otherwise occupied?

TL-N3-2: Do primary drivers of rural households tend to depart earlier to work on their first trip of the day compared to primary drivers from urban or city households?

TL-N3-3: Do trips to work driven on a workday tend to have an earlier first departure time per day compared to trips to work driven on a Saturday or Sunday?

TL-N3-4: Do trips to work driven in wintertime tend to have an earlier first departure time per day compared to trips to work driven in other seasons?

Figure 22 shows that the factor 'main user occupation' has the largest influence on the first departure to work per day. The $||\bar{\delta}||_{\infty}$-value can be denoted as 'medium' based on Cohen's effect size categories. The order of the factor levels indicates that primary drivers who are 'fulltime' occupied or occupied as 'apprentices' (mutually not significant at $\alpha_{local} = 0.05$) have a tendency to depart earlier to work. Therefore the null hypothesis of TL-N3-1 can not be rejected, since there was no significant distinction between 'fulltime' and 'apprentice'.

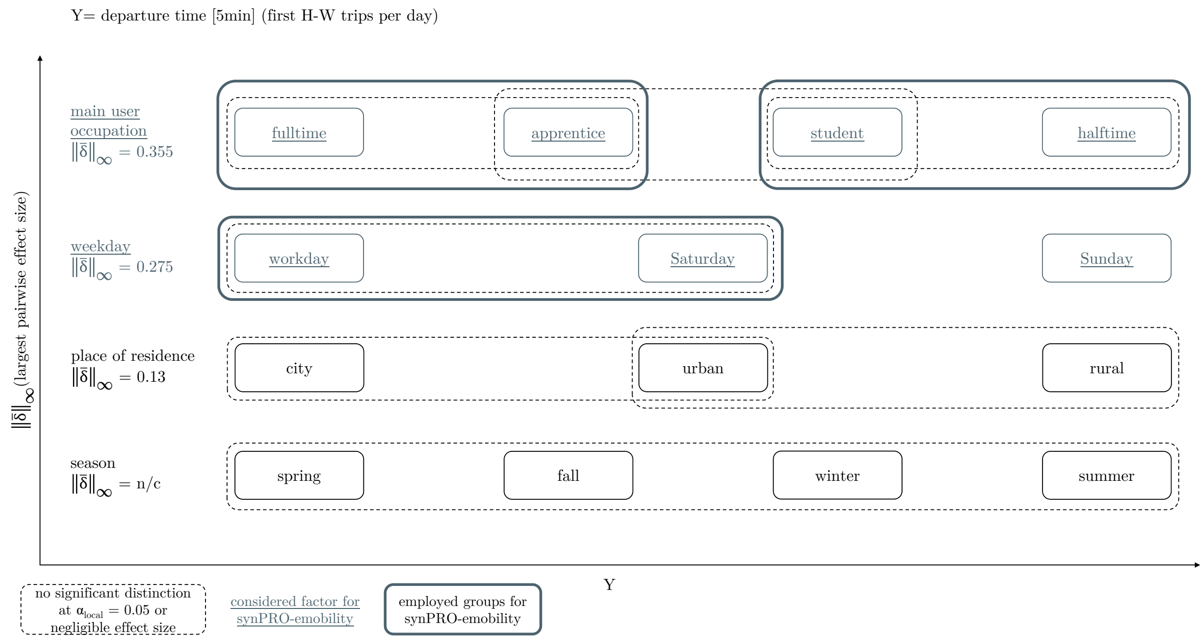


FIGURE 22: TRIP LEVEL: OVERVIEW OF MAIN EFFECTS ON DEPARTURE TIME FOR FIRST H-W TRIPS PER DAY (CF. TABLE 54)

Regarding the factor 'weekday' the factor level order shows that primary drivers tend to depart earlier to work on 'workdays' and 'Saturdays'. Therefore the null hypothesis of TL-N3-3 can not be rejected at $\alpha_{local} = 0.05$. The largest pairwise effect size can be denoted with 'small' using Cohen's effect size categories.

The factor 'place of residence' also has a 'small' largest pairwise effect size. Surprisingly, the factor level order shows that rural households in fact tend to depart later to work than households located in cities or urban areas. Therefore the null hypothesis of TL-N3-2 can not be rejected at $\alpha_{local} = 0.05$.

The factor 'season' showed no pairwise significance at $\alpha_{local} = 0.05$ for any factor level. Therefore the null hypothesis of TL-N3-4 can not be rejected.

With respect to all other first trips per day except H-W trips the following five specified research questions were defined:

TL-N4-1: Do leisure trips tend to have a later first departure time per day compared to trips with other trip purposes?

TL-N4-2: Do trips driven on a day with multiple other trips tend to have an earlier first departure time per day compared to trips driven on a day with fewer trips?

TL-N4-3: Do trips driven on a workday tend to have an earlier first departure time per day compared to trips driven on Saturdays or Sundays?

TL-N4-4: Do trips driven by a primary driver from a rural household tend to have an earlier first departure time per day compared to trips driven by primary drivers from urban or city households?

TL-N4-5: Do trips driven in wintertime tend to have a later first departure time per day compared to trips driven in other seasons?

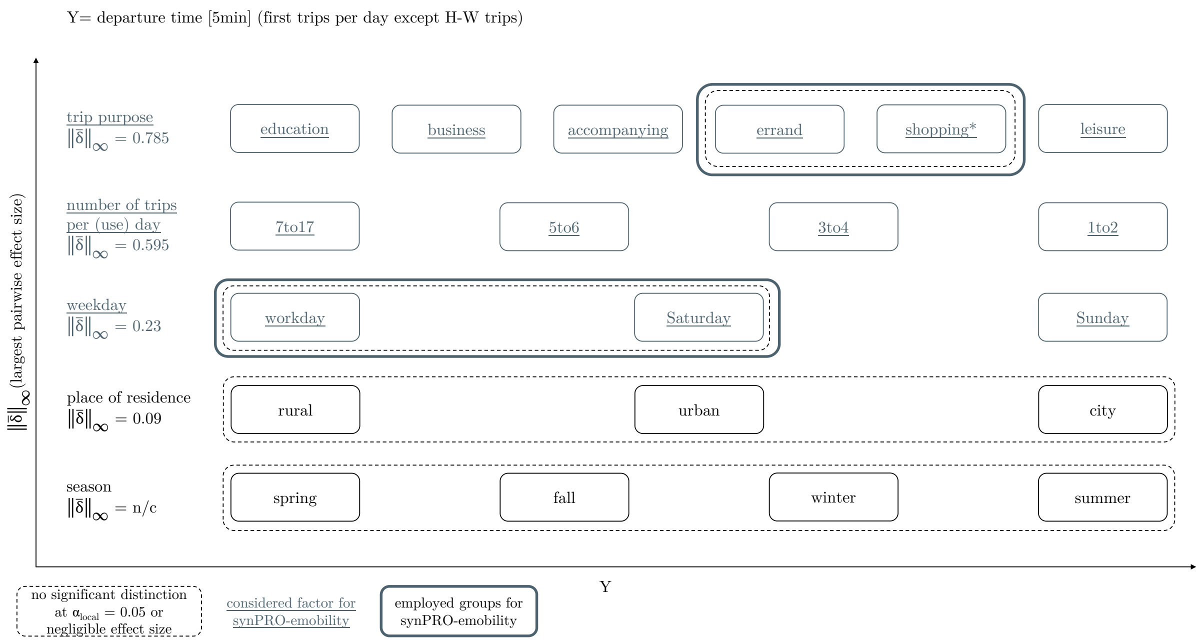


FIGURE 23: TRIP LEVEL: OVERVIEW OF MAIN EFFECTS ON DEPARTURE TIME FOR FIRST TRIPS PER DAY EXCEPT H-W TRIPS (CF. TABLE 55)

Figure 23 shows that the factor 'trip purpose' has the largest pairwise effect on the first departure time per day except H-W trips followed by the factors 'number of trips per (use) day', 'weekday' and 'place of residence'. For the factor 'season' no pairwise comparison was significant at $\alpha_{local} = 0.05$ so that no value was calculated for $||\bar{\delta}||_{\infty}$.

Regarding the factor level order for the factor 'trip purpose' one can see that 'leisure' trips tend in fact to have a later first departure time per day than all other factor levels. The null hypothesis of TL-N4-1 can therefore be rejected at $\alpha_{local} = 0.05$. The largest pairwise effect can be denoted as 'large' based on Cohen's effect size categories.

The factor 'number of trips per (use) day' also has 'large' pairwise effect size. Since a larger number of trips per (use) day is evidently associated with an earlier first departure time per day the null hypothesis of TL-N4-2 can be rejected at $\alpha_{local} = 0.05$. In contrast to the proceeding for the driven distance, here, the 'number of trips per (use) day' is explicitly considered as a variable for synPRO-emobility. More information on the reason for doing so will be given later in Section 4.2.

With respect to the factor 'weekday' one can see that it has a 'small' largest pairwise effect size. The null hypothesis of TL-N4-3 can not be rejected at $\alpha_{local} = 0.05$ as only the factor level group of 'workday' and 'Saturday' tend to have an earlier first departure per day.

The factor 'place of residence' has a 'negligible' largest pairwise effect size. Therefore the null hypothesis for TL-N4-4 can not be rejected at $\alpha_{local} = 0.05$ and the factor is not considered for synPRO-emobility.

Again, the factor 'season' shows any pairwise significant distinction at $\alpha_{local} = 0.05$ between different seasons, so that the null hypothesis of TL-N4-5 can not be rejected.

In order to take a closer look on households' driving behavior with respect to the driving time the following specified research questions were defined:

TL-N5-1: Do primary drivers who are occupied full-time tend to drive longer to work (or from work home) compared to primary drivers who are otherwise occupied?

TL-N5-2: Do primary drivers of rural households tend to drive longer to work (or from work home) compared to primary drivers from urban or city households?

TL-N5-3: Do trips to work (or from work home) driven on a workday tend to have a longer driving time compared to trips to work (or from work home) driven on a Saturday or Sunday?

TL-N5-4: Do trips to work (or from work home) driven in wintertime tend to have a longer driving time compared to trips to work driven in other seasons?

Figure 24 shows that the factor with the largest pairwise effect size is the 'main user occupation'. Following Cohen's effect size categories the effect can be denoted with 'small'. However the the factor level order shows an ambiguous situation where there is no significant distinction of the factor level 'student' compared to all other factor levels. Simultaneously, the three other factor levels each significantly differentiate from one other factor level. This is similar to the situation regarding the driven distance for H-W or W-H trips. Again, taking a closer look on the respective test table (cf. Table 56) one can see that this test situation is most likely due to drastically decreased power as described before. For consistency reasons the factor level groups employed for synPRO-emobility are adopted from the dependent variable driven distance.

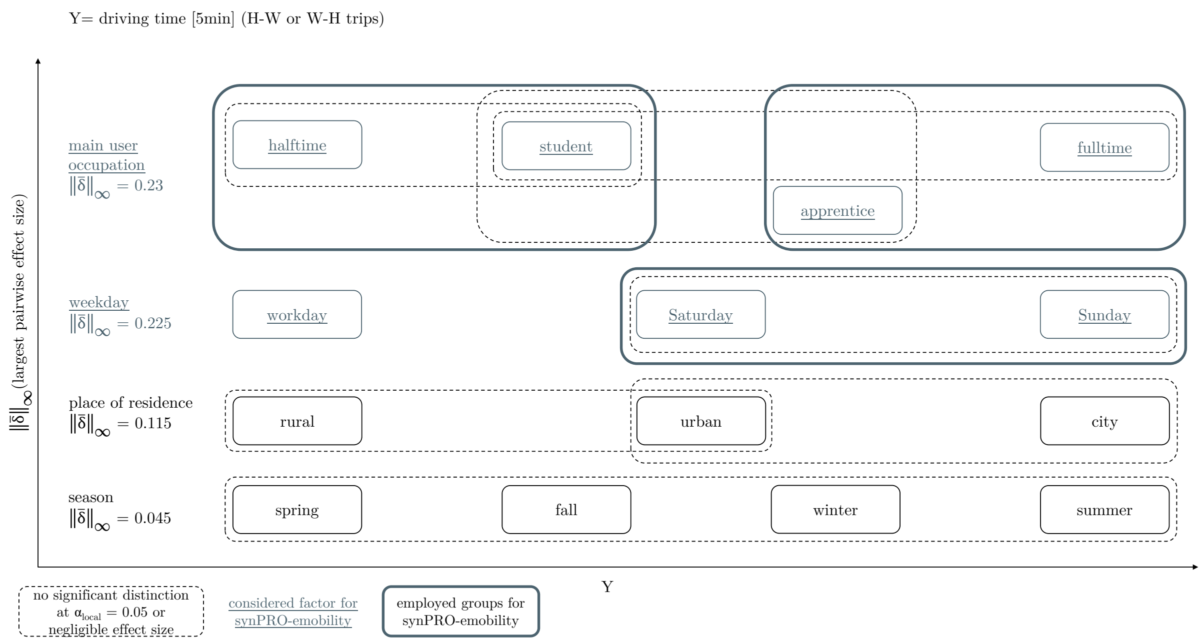


FIGURE 24: TRIP LEVEL: OVERVIEW OF MAIN EFFECTS ON DRIVING TIME FOR ALL H-W OR W-H TRIPS (CF. TABLE 56)

Regarding the factor ‘weekday’ one can see, that is also has a ‘small’ effect size based on Cohen’s effect categories. Surprisingly, the factor level order suggests an opposite effect that trips from home to work or back on a ‘workday’ have a shorter driving time than for ‘Saturdays’ or ‘Sundays’. Therefore the null hypothesis for TL-N5-3 can not be rejected at $\alpha_{local} = 0.05$.

The factor ‘place of residence’ has barley a ‘small’ largest pairwise effect size based on Cohen’s effect size categories. The ordering of the factor levels shows that the null hypothesis of TL-N5-2 can not be rejected at $\alpha_{local} = 0.05$ since there is no significant distinction between the factor levels ‘rural’ and ‘urban’. Even though having a ‘small’ largest pairwise effect size the factor was not considered for synPRO-emobility due to sample size limitations.

The factor ‘season’ does not provide a significant and non-negligible effect for at least one pairwise comparison as it was also the case for the driven distance as well as the the first departure time per day no matter if trips are restricted to H-W or W-H trips or not.

Next, the driving time is also differentiated for trips except H-W or W-H trips. For that matter the following five specified research questions were defined:

TL-N6-1: Do leisure trips tend to have a longer driving time compared to trips with other trip purposes?

TL-N6-2: Do outside city trips tend to have a longer driving time compared to inside city trips?

TL-N6-3: Do trips driven on a day with multiple other trips tend to have a smaller driving time compared to trips driven on a day with fewer trips per (use) day?

TL-N6-4: Do trips driven on a workday tend to have a shorter driving time compared to trips driven on a Saturday or Sunday?

TL-N6-5: Do trips driven in wintertime tend to have a shorter driving time compared to trips driven in other seasons?

Figure 25 shows that the factor ‘trip purpose’ which has a ‘large’ effect size following Cohen’s effect size categories. The factor level order suggests that the null hypothesis of

TL-N6-1 can not be rejected at $\alpha_{local} = 0.05$ since a 'leisure' trip tends to have shorter driving time compared to 'business' or 'education' trips. This result is consistent with the result yielded by the analysis of the dependent variable 'driven distance'.

The factor 'trip distance category' also has a 'large' value for $||\bar{\delta}||_\infty$ based on Cohen's categories. As for the driven distance, a longer driving time is clearly associated with an 'outside city' trip compared to all other factor levels so that the null hypothesis of TL-N6-2 can be rejected at $\alpha_{local} = 0.05$.

Regarding the 'number of trips per (use) day' the results equal those for dependent variable 'driven distance'. Trips driven on a day with multiple other tips tend to have a shorter driving time compared to a day with a lower number of trips. Therefore the null hypothesis of TL-N6-3 can be rejected at $\alpha_{local} = 0.05$. However, as it was already described for the driven distance, this factor is not considered directly as a variable for synPRO-emobility. Instead it is indirectly considered making use of a rejection algorithm approach (cf. Section 4.2).

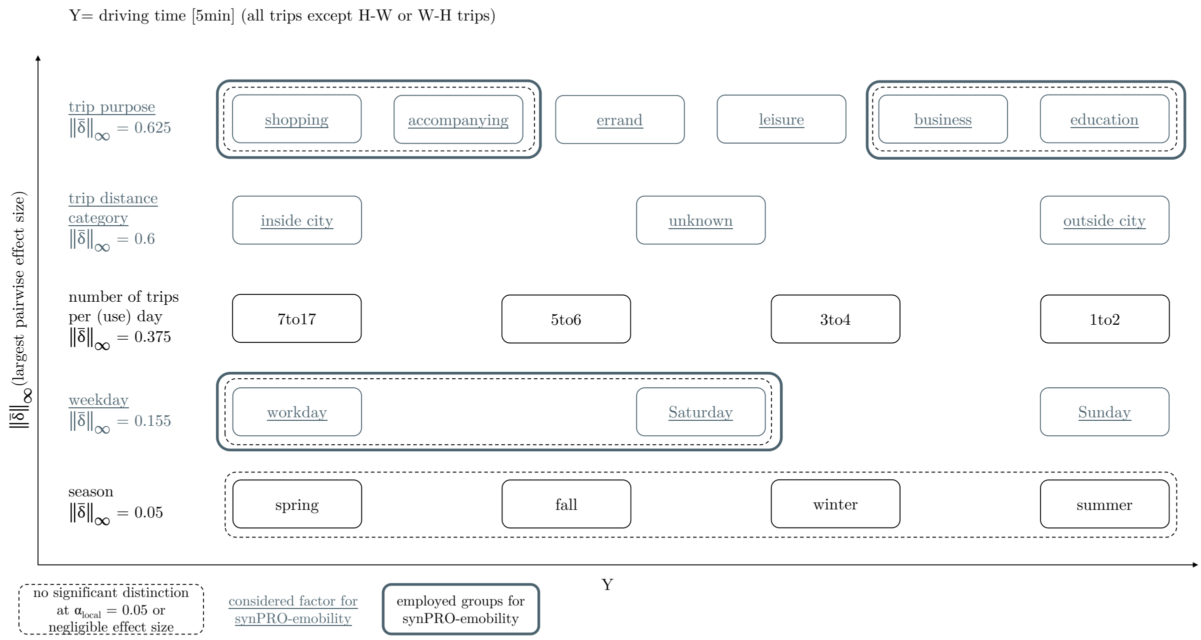


FIGURE 25: TRIP LEVEL: OVERVIEW OF MAIN EFFECTS ON DRIVING TIME FOR ALL TRIPS EXCEPT H-W OR W-H TRIPS (CF. TABLE 57, 58, 59)

The factor 'weekday' has a 'small' largest pairwise effect size. The factor level order suggests that the null hypothesis of TL-N6-4 can not be rejected since the factor levels 'workday' and 'Saturday' are mutually insignificant at $\alpha_{local} = 0.05$.

The factor 'season' is again not significant or has only a 'negligible' effect size based on Cohen's effect size categories for any factor levels. Therefore the null hypothesis for TL-N6-5 can not be rejected at $\alpha_{local} = 0.05$.

To differentiate households' driving behavior regarding the parking for H-W trips the following two specified research questions were defined:

TL-N7-1: Do primary drivers who are occupied full-time tend to park longer at work compared to primary drivers who are otherwise occupied?

TL-N7-2: Do trips to work driven on a workday tend to park longer at work compared to trips to work driven on a Saturday or Sunday?

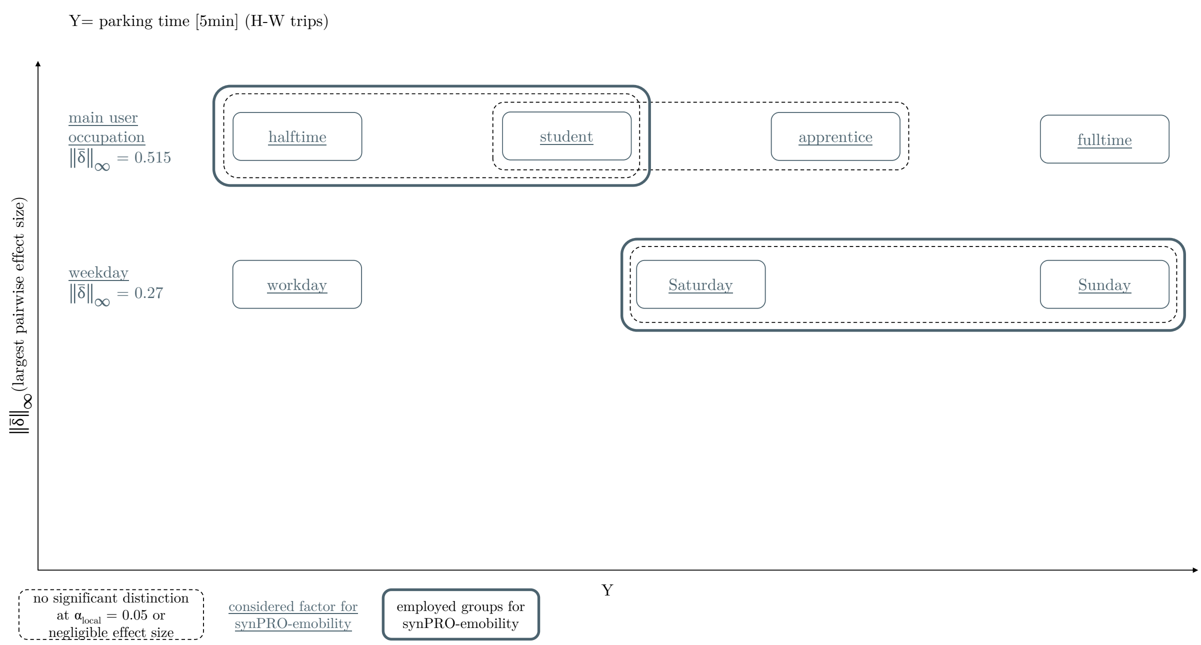


Figure 26: Trip level: overview of main effects on parking time for all H-W trips (cf. Table 60)

Figure 26 shows that the null hypothesis of TL-N7-1 can be rejected at $\alpha_{local} = 0.05$ since primary drivers who are 'fulltime' occupied clearly differentiate from all other factor levels. The largest pairwise effect size based on Cohen's effect size categories can be denoted with 'large' for the factor 'main user occupation'.

Regarding the factor ‘weekday’, which has a ‘small’ largest pairwise effect size based on Cohen’s categories, the null hypothesis of TL-N7-2 can not be rejected at $\alpha_{local} = 0.05$ since the since trips driven on ‘workdays’ tend in fact to have a shorter parking time compared to trips driven on ‘Saturdays’ or ‘Sundays’. For example, this result could be due to the fact that people tend to park their cars at work for a whole weekend or present at the workplace for standby.

At last, a further differentiation of households’ driving behavior is presented by defining specified research questions for the parking time of all trips except H-W trips:

TL-N8-1: Do leisure trips tend to have a longer parking time compared to trips with other trip purposes?

TL-N8-2: Do trips driven on a day with multiple other trips tend to have a parking time compared to trips driven on a day with fewer trips per (use) day?

TL-N8-3: Do trips driven on a workday tend to have a shorter parking time compared to trips driven on a Saturday or Sunday?

TL-N8-4: Do trips driven in wintertime tend to have a shorter parking time compared to trips driven in other seasons?

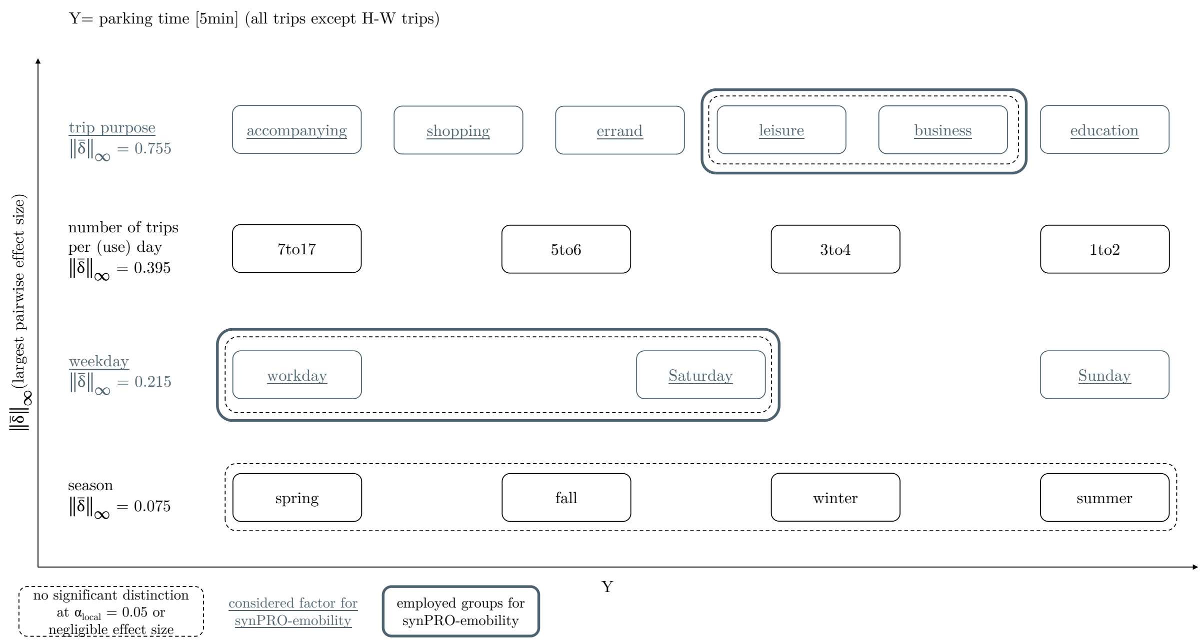


FIGURE 27: TRIP LEVEL: OVERVIEW OF MAIN EFFECTS ON PARKING TIME FOR ALL TRIPS EXCEPT H-W OR W-H TRIPS (CF. TABLE 61, 62, 63)

Figure 27 shows that the factor ‘trip purpose’ has the largest pairwise effect on the parking time upon all tested influencing factors followed by the factor ‘number of trips per (use) day’, ‘weekday’ and ‘season’.

Regarding the factor ‘trip purpose’ one can see that it has a very large effect on the parking time due to a $||\bar{\delta}||_\infty$-value which can be denoted with ‘large’ based on Cohen’s effect size categories. However, the null hypothesis of TL-N8-1 can not be rejected at $\alpha_{local} = 0.05$ since trips with the trip purpose ‘education’ tend to have a longer parking time than all other factor levels.

With respect to the factor ‘number of trips per (use) day’ it is again noticeable that trips driven on days together with multiple other trips tend to have a shorter parking time than trips driven on days with only a few other trips. Therefore the null hypothesis of TL-N8-2 can be rejected at $\alpha_{local} = 0.05$.

The factor ‘weekday’ has a ‘small’ largest pairwise effect size following the effect size categories of Cohen. The ordering of factor levels shows that the null hypothesis of TL-N8-3 can not be rejected since there is no significant distinction between the factor levels ‘workday’ and ‘Saturday’ at $\alpha_{local} = 0.05$. However, the null hypothesis could be rejected if these two factors are grouped.

The factor ‘season’ is again either not significant or has only a ‘negligible’ effect size based on Cohen’s categories for any factor levels. Therefore the null hypothesis of TL-N8-4 can not be rejected at $\alpha_{local} = 0.05$.

The differentiation of households’ driving behavior regarding numerical dependent trip variables yielded in many cases medium to large effects for the influencing factor ‘trip purpose’. Therefore it is also analyzed as a categorical dependent trip variable together with the variable ‘departure arrival place’ (cf. Table 7). The latter is analyzed first using three specified research questions concerning the statistical dependency on different influencing factors, followed by one that relates to the dependency of both categorically dependent variables.

TL-C1-1: Is the trip's departure and arrival place dependent on the main user's occupation?

The influence of the factor 'main user occupation' on the dependent variable 'from...to' is shown in Figure 28. One can see, that both variables significantly dependent on each other based on a χ^2-test of independence at $\alpha_{local} = 0.05$. The null hypothesis for TL-C1-1 can therefore be rejected. Based on Cramer's V the association can be described as barely 'small'. Looking closer into the dependency structure using the mosaic plot it is noticeable that primary drivers who are 'fulltime' occupied are less likely to depart or arrive at places somewhere inside or outside there own city or town (red shaded tiles in row 2 counting from above).

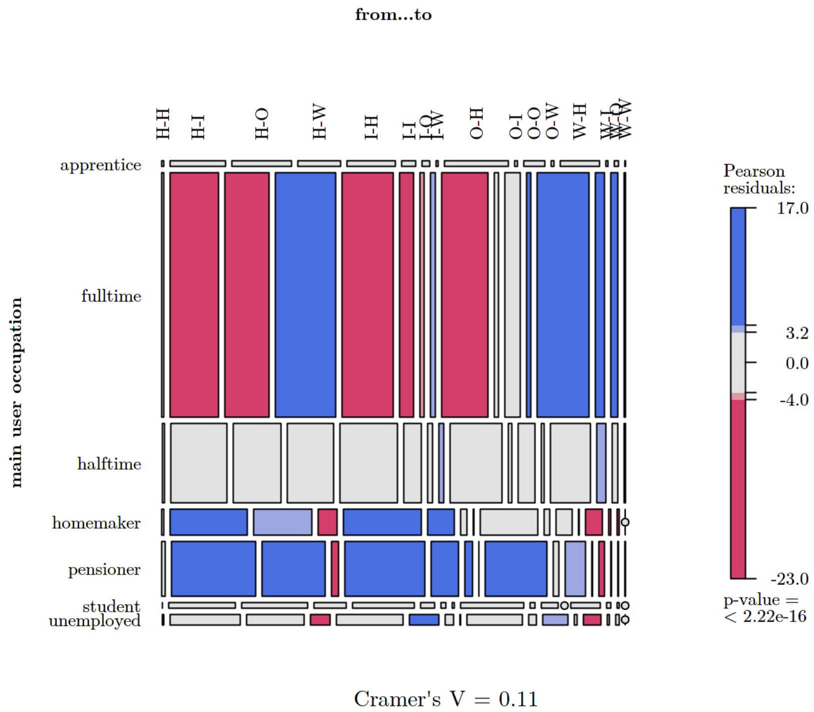


FIGURE 28: TRIP LEVEL (χ^2-TEST AND MOSAIC PLOT): MAIN EFFECT OF MAIN USER OCCUPATION ON DEPARTURE ARRIVAL PLACES

Instead they are more likely to depart or arrive at their workplace (blue shaded tiles in row 2 counting from above). The contrary applies for primary drivers occupied as 'pensioners' or 'homemakers'. 'Apprentices', 'students' as well as 'halftime' occupied primary drivers show similar conditional probabilities for the respective departure and arrival places which hardly deviate from statistical independence. 'Unemployed' primary drivers stand slightly apart as their probability to arrive or depart from workplaces is reduced in favor of an increased probability to cover trips departing and arriving somewhere inside (I-I) or outside

(O-O) their own city or town.

TL-C1-2: Is the trip's departure and arrival place dependent on the trip index?

From Figure 29 one can see the that the factor 'from...to' is statistically dependent on the factor 'trip index' based on a χ^2-test of independence at $\alpha_{local} = 0.05$. The null hypothesis of TL-C1-2 can therefore be rejected. Based on Cramer's V and Cohen's effect size categories the overall association between these two factors can be described as 'large'.

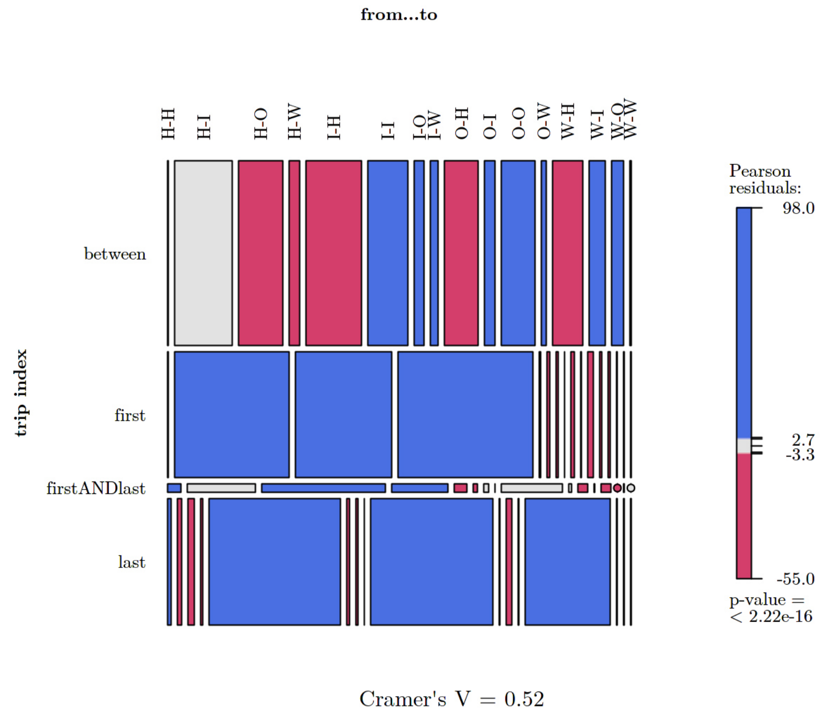


FIGURE 29: TRIP LEVEL (χ^2-TEST AND MOSAIC PLOT): MAIN EFFECT OF TRIP INDEX ON DEPARTURE ARRIVAL PLACES

The mosaic plot clearly shows that it is more much more likely that the first trip of a particular day departs from home and that the last arrival per day is also at home. Compared to that it is more likely that trips in between have a departure or arrival place inside or outside of the primary driver's own city or town. When just considering in-between trips they have most likely a departure or arrival place at home and somewhere inside city (H-I, I-H) followed by trips with a departure or arrival place at home and somewhere outside city (H-O, O-H) and trips between places somewhere inside or outside city (I-I, O-O). If there is only one trip on a particular day (cf. 'firstANDlast') it is most likely that the primary driver moves the car to a place outside city or to his workplace.

TL-C1-3: Is the trip's departure and arrival place dependent on the trip's weekday?

Figure 30 shows the relation of the dependent variable 'from...to' and the factor 'weekday'. The result of the χ^2-test of independence at $\alpha_{local} = 0.05$ clearly point to a statistical dependence of the involved variables. Based on Cramer's V and Cohen's effect size categories the association can be denoted with 'small'.

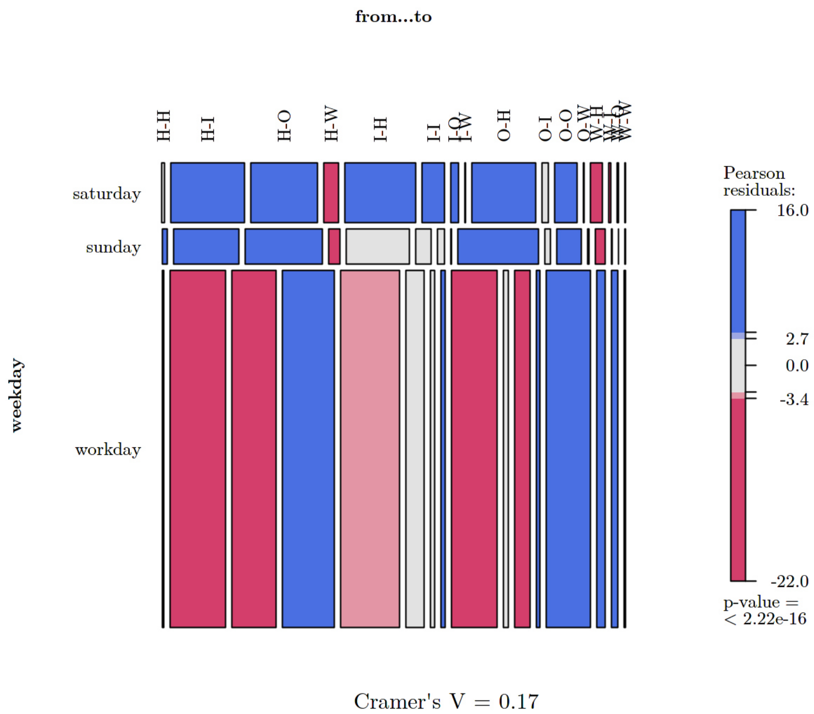


Figure 30: Trip level (χ^2-test and mosaic plot): main effect of weekday on departure arrival places

The mosaic plots reveals that trips from home to the workplace or reversed (H-W, W-H) occur less likely on the weekend compared to workdays. However, they still exist. This could be due to the fact that specific occupational groups have to work on the weekend just as well as on typical workdays, for example those who are on standby (e.g. policemen, firefighters, doctors, paramedics). Simultaneously, it is noticeable that primary driver's tend to drive more frequently to destinations outside their own city or town on Saturdays or Sundays (blue shaded tiles in row 1 and 2 counting from above) compared to workdays.

TL-C2-1: Is the trip's purpose dependent on the trip's departure and arrival place?

From figure 31 one can see that the dependent variable 'trip purpose', which is itself an influencing factor for the most analyzed numerically dependent variables, is dependent on the other categorical dependent trip variable 'from to' based on a χ^2-test of independence at $\alpha_{local} = 0.05$. The association can be denoted with 'medium' based on Cramer's V and Cohen's effect size categories.

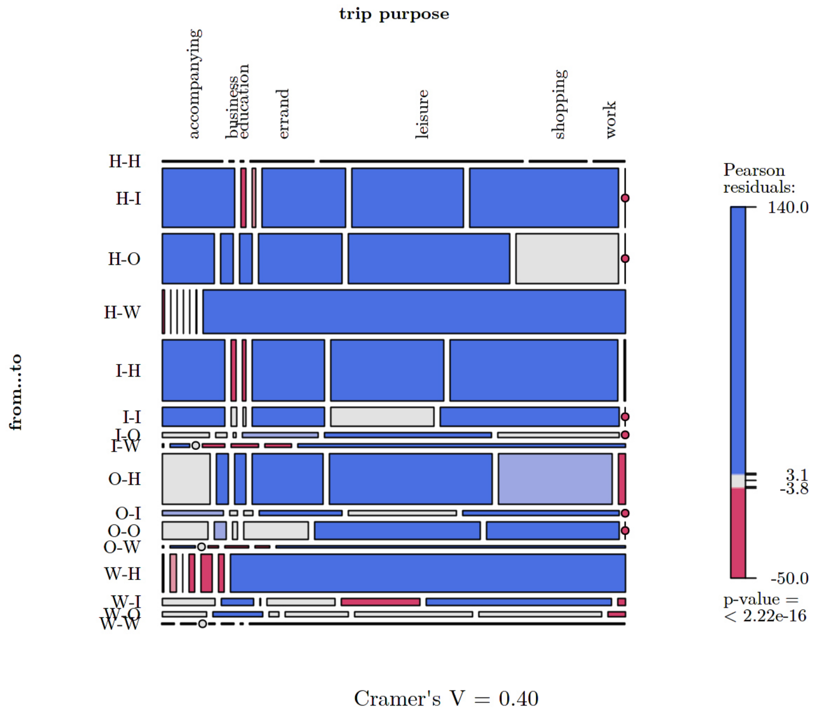


Figure 31: Trip level (χ^2-test and mosaic plot): main effect of departure arrival places on trip purpose

The mosaic plot reveals that trips with an arrival or departure place somewhere inside city (H-I, I-H, I-I) are strongly associated with the trip purposes 'accompanying', 'errand', 'leisure', and 'shopping' while the trip purposes 'business', 'education', and 'work' are very unlikely. Compared to that, trips with an outside city departure or arrival place (H-O, O-H, O-O) have a higher chance to have an 'business', 'education' or 'work' trip purpose. Regarding the trips from the workplace to an arrival place somewhere inside city (W-I) a 'shopping' trip purpose is most likely while the trip purposes 'leisure' and 'shopping' are almost equal regarding an arrival place somewhere outside city (W-O). Comparing both cases to other departure and arrival combinations 'business' trips are more likely to occur. The trips to work departing from home or a place somewhere inside or outside the primary driver's own city or town (H-W, I-W, O-W) are all most likely to have the trip purpose 'work'. Same applies for the trip from work back to home (W-H). The existence of other trip purposes for these departure arrival combinations indicates either that some survey participants reported ambiguous trip purposes or that the proceeding to assign departure and arrival places to a particular trip was not exact to a full extend (cf. Section 3.1.2).

Trips with a departure outside city and an arrival inside city (O-I) are mostly associated with the trip purpose 'shopping', wile it is 'leisure' for the reversed case (I-O). Trips with a departure at work and an arrival at work (W-W) are mostly associated with work trips. For example these trips could be errands with an occupational character. Concerning trips with a departure at home and an arrival at home (H-H) 'leisure' is the most likely trip purpose.

3.3.4 Critical summary

The analysis provided detailed information on households' driving behavior in Germany, based on χ^2-tests of independence and pairwise comparisons using Cliff's method. Due to the large number of tested hypotheses and the therefore arising multiple comparison problem, the results were adjusted using the Holm-Bonferroni's FWER correction method at $\alpha_{local} = 0.05$ (for the definition of 'local' see Section 3.2.2). Results on all hypothesized relations are summarized in Table 64–68 in A.6. The influencing factors for the subsequent implementation of the results in the simulation model (Chapter 4) were considered in descending order according to their largest pairwise effect sizes (except 'negligible' effects). However, they were only included, if the sample size in the factor level group was larger than 30.

First, the number of cars available in a household seems to be strongly influenced by the economic household status and the household type. Results suggest that a higher number of cars is associated with higher incomes and family households (with minimum one underage or adult child neglecting single parent households) when averaging across all levels of other factors. Even when controlling for specific factor levels the result remains unchanged. The place of residence with regard to agglomerations (rural, urban, city, cf. (Adam et al., 2005)), seems to have only a small influence proposing that households in rural or urban areas have more cars available compared to city areas. This result is robust in terms of interaction effects, e.g. controlling for family households, which are more likely in rural or urban areas.

Second, the main effects (i.e. the effect of a factor on a dependent variable averaging across the levels of any other factor) on the number of trips per (vehicle use) day seem to have the factors weekday, vehicle use frequency, household type and main user occupation

which all can be denoted as small. Averaging across all levels of other factors, more trips per day seem to be covered on workdays or Saturdays compared to Sundays. A daily vehicle use frequency tends to be associated with a higher probability to cover more trips per (vehicle use) day compared to a weekly and even rarely vehicle use frequency.
Family households (with one or more underage children) tend to undertake more trips than non-family households. Halftime employed, unemployed and homemakers seem to display a larger number of trips per (vehicle use) day than students, pensioners, apprentices and full-time employed. Most results are stable when controlling for specific levels of other involved factors. However, results on the main user occupation are insignificant when controlling for Sundays. Additionally, when controlling for the type of a household (i.e. family and non-family households), the number of trips by pensioners and students is no longer significantly different from other groups in the "user occupation" variable. The household's economic status, the place of residence as well as the season do not have a statistically significant impact on the number of trips per (vehicle use) day or are negligible in magnitude.
Regarding the (vehicle) use frequency, associations with the household type and the main user occupations are noticeable but relatively small. Family households are slightly more likely to have a daily vehicle use frequency compared to statistical independence, whereas pensioners are clearly less likely to have one. Other household types are rather close to statistical independence. Simultaneously, main users that are full-time or halftime employed or are apprentices are more likely to use the car on a daily basis, while homemakers and pensioners are less likely to do so. Students and unemployed are rather close to statistical independence. Associations regarding the place of residence are negligible.
Concerning the main user (daily vehicle) use, associations with the weekday and the main user (vehicle) use frequency exist. A vehicle use is more likely on workdays followed by Saturdays and Sundays when other factors are not considered. Concurrently, a more frequent (vehicle) use is clearly associated with a higher probability to use the car on a particular day, whereas the household's place of residence again has only a negligible influence.

Third, the driven distance and driving time for trips between home and the workplace seem to be mildly influenced by the main user occupation. However, the results are ambiguous upon different occupational groups. This is most likely due to the smaller and highly deviant sample sizes for the involved factor levels lowering the statistical power of

Cliff's method. The place of residence has only a negligible effect on the driven distance, but was significant together with a small effect size regarding the driving time for city households compared to rural households. Additionally, the driving time to work seems to be influenced by the weekday as it is (contrary to the hypothesized relation) longer on the weekend than during the week. This might be explained by the fact that people who have to work on the weekend drive longer distances to work on average. The season has only a negligible influence on the the driving time to work.

The driven distance and driving time for all non-work trips are largely influenced by the trip purpose and the trip distance category. Business trips or trips with an educational purpose (trips to school or the apprenticing company) seem to have the longest driven distance and driving time followed by leisure trips, errands, shopping trips and trips with the purpose to accompany other persons. Furthermore, a medium effect is given by the number of trips per (use) day, influencing both quantities negatively so that more trips per day are associated with shorter driven distances and driving times. This effect was confirmed by the corresponding correlation found during exploratory data analysis (cf. Figure 61 in B.1) but is more indirect lacking explanatory power on causal relations why the driven distance and driving time is shorter. Hence, it was not considered as a direct influencing factor for the modeling in Chapter 4 but rather considered by using a certain way of generating driving profiles. A small effect on both quantities is also given by the weekday as trips on workdays or Saturdays tend to be shorter than on Sundays whereas the seasons only have a negligible effect.

The first departure time to work is largely influenced by the main user occupation showing that occupied full-time primary drivers together with apprentices tend to depart earlier to work than halftime occupied primary drivers or students. Moreover, trips on a workdays or Saturdays tend to have an earlier first departure to work compared to Sundays. In contrary to the hypothesized relation, first trips to work in city or urban areas tend to be earlier than in rural areas. The seasons do not have any significant effect on the first departure to work.

Regarding all non-work trips, the first departure time per day is strongly influenced by the trip purpose and and the number of trips per (use) day. In this case, latter is considered as an explicit variable for the modeling in Chapter 4 since a direct causal relation between an earlier departure and the primary driver's knowledge of the number of trips to be covered on a particular day seems valid. Equal to the result for the first departure to work non-work trips on workdays or Saturdays tend to have an earlier departure than on Sundays. The factor place of residence only has an negligible influence on the first departure per day. The seasons do again not have any significant effect.

Parking times at work are primarily influenced by the main user occupation indicating that primary drivers halftime occupied or occupied as students as well as apprentices park significantly shorter at work compared to full-time occupied primary drivers. Additionally, the weekday is crucial since parking events on the weekend are significantly longer than on workdays. This is most likely explainable by the fact, that some participants have parked their car at work over the weekend.
Regarding all parking events at other places than at work, the trip purpose plays a major role providing a very large effect size. Parking events with the trip purpose education tend to be longer than for any other trip purpose. Also, the weekday at which the vehicle is parked does influence the parking duration. On Sundays it tends to be longer compared to workdays or Saturdays.

Overall, the factor place of residence or season have only a negligible to small influence on all analyzed dependent variables or were not significant for any factor level comparison. With regard to the place of residence this result confirms the findings of Babrowski et al. (2014, p. 283) saying that "neither national nor regional differences" have a strong influence relying on the same behavioral data for Germany.

Viewing all hypotheses on numerically dependent variables throughout this analysis as one *intersection hypothesis* of simultaneous statistical inference (Dickhaus, 2014), there is a very high overall chance of making *false positive* (type I error) or *false negative* (type II error) discoveries due to the multiple comparison problem at hand and the proceeding to adjust p-values locally (cf. Section 3.2.2). It is therefore very likely that detected effects are not present concerning the population of the analysis (i.e. all vehicle main users of private households in Germany) or that effects regarding the analyzed influencing factors exist but were not detected. This is not the case for hypotheses on categorically dependent variables, though, as their p-values (p=2.22e-16) are even significant at $\alpha_{global} = 0.05$ using a *global* Bonferroni correction for all pairwise comparisons throughout this work. However, as the first research question advocates it was not the goal of this analysis to reliably infer simultaneously from all test results that statistically significant effects are present in the population but to detect patterns in the sample (that might alone be significant for the population) and provide a possible differentiation that helps to discuss effects and may lead to generalization of findings on households' driving behavior in Germany following a rather *inductive* research approach. In order to reliably deduce population effects from presented sample effects it is necessary to collect further data and test selected influencing factors presented – ideally those with large $||\bar{\delta}||_\infty$-values – with respect to the new data (cf. MiD inquiry 2016 in Section 3.1.1).

4 Implementation of synPRO-emobility

This chapter first gives an overview of the developed simulation model illustrating the model's goal and approach, the overall structure of the model, the input data as well as information on the model output. Next the process to determine synthetic BEV charging load profiles is described, answering the second research question (cf. Chapter 1) and highlighting the possibilities and limitations of the method. Finally, results on simulated charging profiles are provided and compared to simulation results based on empirical charging data of three EV fleets in Southwest Germany, answering the third research question of this work. The chapter closes with a critical appraisal on the validity of the presented simulation results.

4.1 Model overview

4.1.1 Goal and approach

The goal of the modeling is to extend the existing approaches mentioned in Section 1 by considering different socio-economic and sociodemographic household characteristics, different possible charging decisions and locations in order to allow for a more differentiated and behavior-oriented characterization of BEV charging profiles. The synthetic BEV charging load profiles can be applied to, for example, grid simulations, electricity consumption studies, assessment of direct load controlled BEV charging as well as design of smart charging strategies under uncertainty.

As synPRO builds the framework for the BEV charging model, it shares its modeling approach and several key features: synPRO is designed based on a stochastic bottom-up approach using survey data, capable of generating holistic electrical and thermal households' load profiles using the programming language R (R Core Team, 2017). Socio-economic and sociodemographic aspects such as number of household members, their working pattern and the number of available devices in the household are considered in the model, which have been found valuable features. Once the device stock of a household and the number of usages per day is determined, subsequent sampling of start times and correlated usage lengths of predefined activities, e.g. doing laundry, are mapped with devices of different categories and load traces. The model output are load profiles with a time resolution of 10 seconds, a socio-economic differentiation, a distinction of work and weekend days, consideration of holidays and vacations. Seasonal effects are considered using changing probability sets during the course of the year.

The BEV charging model, called synPRO-emobility, is based upon this stochastic bottom-up approach using recent survey data for German households to derive differentiated driving behavior in Germany. Once the number of available BEV per household given a specific market penetration rate is determined, a certain occupation type together with a corresponding vehicle use frequency is assigned to each BEV's primary driver. Additionally, a BEV model together with its technical properties is sampled.

In a first subsequent step the daily use or disuse of a particular BEV (and corresponding primary driver) is sampled for all days of a year considering holidays as well as vacation periods for the desired simulation year. Next, the number of trips per use day is sampled and an inhomogeneous first-order Markov chain (inhomogeneous regarding the trip index per day and different weekdays) constructs a logically consistent sequence of departure and arrival places for all trips of a year. These trips are then enriched with trip purpose information and finally rated with driven distances, driving as well as parking times. A sampling of the departure of the first trip per day allows for the calculation of all departure and arrival times of the remaining trips per day using the temporal information of the step before.

The generated driving profiles are then used to calculate the vehicle's battery state-of-charge (SOC) before and after a trip based on its specific consumption per 100 kilometers, starting with a fully charged battery on the first simulation day. After covering the previously sampled distance the driver decides for every parking event at a possible charging station (cf. Section 2.4) if he is willing to connect the BEV to the grid or not based on the current SOC of the battery. This step is modeled using differently parametrized *univariate logit models* allowing for different preferences to charge at different locations. Once the BEV is connected to the grid the battery is charged until being fully charged or until the user interrupts the charging process to leave for a new destination. The main output of synPRO-emobility are load profiles for different typical charging locations with a minimum time resolution of 10 seconds. Further information on the input data and the model output as well as the modeling and calculations to simulate the described behavior are given in the next sections.

4.1.2 General structure

The general structure of synPRO-emobility can be subdevided into five distinct steps, while step 3 and 4 are iteratively repeated for every parking event as shown in Figure 32. First, the input data of the model granting a set of household or BEV configurations, both categorically and numerically differentiated information on driving behavior of individual households or primary drivers, as well as behavioral decision parameters for the grid connection and the charged energy are imported into the model. Further information on the input data will be given in the next subsection.

Second, driving profiles for every household's BEV (or primary driver respectively) are generated, resulting in a consistent sequence of departure and arrival places rated with driven distances, driving times and parking times. These profiles allow for scheduling the maximum start and end time of charging events. Detailed information on factors influencing the driving behavior were presented in Chapter 3 and will be summarized in the next subsection. Information on how the driving profiles are generated will be provided in Section 4.2.1.

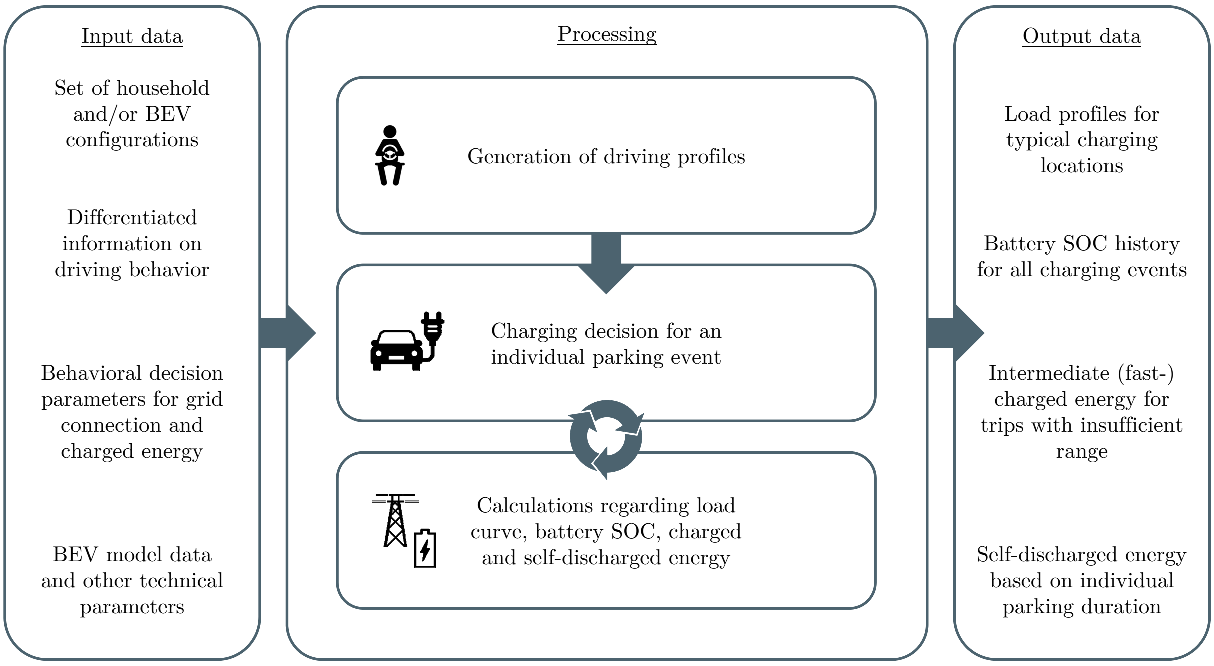


Figure 32: General structure of synPRO-emobility

Third, decisions on the grid connection as well as the charged energy (if connected) are taken based on the corresponding behavioral parameters. Further information on how the decision taking is modeled, are given in Section 4.2.2.

Fourth, calculations regarding the load curve for the charged energy, the vehicle's battery state-of-charge as well as the self-discharged energy are performed for all parking locations. Assumption for the calculations are presented in in the next section (cf. 4.1.3).

Fifth, a final step saves simulated load profiles for typical charging locations (aggregated for several BEVs or separately) as well as important information for individual trips and parking events such as a battery SOC history, intermediate (fast-) charged and self-discharged energy amounts (cf. Section 4.1.4)

4.1.3 Input data

Household and BEV configurations

An input table allows the synPRO-emobility user to create a set of desired households or BEVs for the simulation and specify up to 17 parameters for particular households or BEVs (cf. Figure 33). One can simulate multiple households or BEV of the same type by adjusting the parameter 'quantity'. Theoretically speaking, every input line consists of a set of user-defined *deterministic* or *stochastic* household related parameters and a set of user-defined *deterministic* or *stochastic* BEV related parameters. The choice of a certain set of deterministic household parameters p_d^{HH} determines the characteristic for all households of the respective row. Accordingly, the choice of a certain set of deterministic BEV parameters p_d^{EV} determines the characteristic for all households' BEV of the respective row. Therefore, depending on the 'quantity', every row either represents an individual household (if 'quantity' = 1) of the type p_d^{HH} with a fixed or sampled number of BEV ('emob_number_of_ev' = 1, 2, 3 or 'sampling') of the type p_d^{EV} or multiple households (if 'quantity' > 1) of the type p_d^{HH} with a sampled number of BEVs of the type p_d^{EV}. If any deterministic parameters are set, either on the household level or on the vehicle level, the respective characteristics are sampled and represent the empirical distributions determined in Section 3 asymptotically (i.e. for a large number of simulation runs).

In general, note that sampled characteristics do not necessarily mean that one obtains a statistically representative or an average output, since one might draw several outliers by chance. Outliers themselves are not "false" data since they result from causal relations in reality and are sometimes of most interest when conducting an analysis of simulation results. Therefore following the laws of large numbers one has to increase the parameter 'quantity' to minimize serious deviations from the empirical distributions on average.

```
##########################################################################################
## In order to start the simulation set all parameters in the synpro.config.R and hit the "Source" button.
##########################################################################################
# Column 01: quantity
# Column 02: emob_hh_economic_status
# Column 03: emob_hh_type
# Column 04: emob_hh_place_of_residence
# Column 05: emob_hh_number_of_ev
# Column 06: emob_ev_main_user_occupation
# Column 07: emob_ev_main_user_use_frequency
# Column 08: emob_ev_model
# Column 09: emob_ev_p_nominal_home_kw
# Column 10: emob_ev_p_nominal_work_kw
# Column 11: emob_ev_p_nominal_pop_kw
# Column 12: emob_ev_p_nominal_other_kw
# Column 13: emob_ev_connecting_neutrality_soc_home
# Column 14: emob_ev_connecting_neutrality_soc_work
# Column 15: emob_ev_connecting_neutrality_soc_pop
# Column 16: emob_ev_connecting_neutrality_soc_other
# Column 17: emob_ev_connecting_sensitivity
# Column 18: emob_ev_charging_energy_strategy

# Experience value for simulations: 30 seconds per profile (saving single and aggregated output files)

quantity;emob_hh_economic_status;emob_hh_type;emob_hh_place_of_residence;emob_hh_number_of_ev;emob_ev_main_user

#1#2          #3     #4     #5   #6                    #7         #8             #9         #10        #11        #12
100;"sampling";"sampling";"sampling";"1";"sampling";"sampling";"sampling";"sampling";"sampling";"sampling";"sam
100;"sampling";"sampling";"sampling";"1";"fulltime";"sampling";"sampling";"sampling";"sampling";"sampling";"sam
100;"sampling";"sampling";"sampling";"1";"halftime";"sampling";"sampling";"sampling";"sampling";"sampling";"sam
100;"sampling";"sampling";"sampling";"1";"apprentice";"sampling";"sampling";"sampling";"sampling";"sampling";"s
100;"sampling";"sampling";"sampling";"1";"homemaker";"sampling";"sampling";"sampling";"sampling";"sampling";"sa
100;"sampling";"sampling";"sampling";"1";"pensioner";"sampling";"sampling";"sampling";"sampling";"sampling";"sa
100;"sampling";"sampling";"sampling";"1";"student";"sampling";"sampling";"sampling";"sampling";"sampling";"samp
100;"sampling";"sampling";"sampling";"1";"unemployed";"sampling";"sampling";"sampling";"sampling";"sampling";"s
```

Figure 33: Example overview of household/BEV configurations for a simulation in synPRO-emobility

Differentiated information on driving behavior

The input data regarding the differentiated driving behavior is first structured by the different units of observation used throughout this work and then subdivided by the statistical data type of the different dependent variables (categorical or numerical).

Categorical data is incorporated into synPRO-emobility as *contingency tables* (cf. Section 3.2.1) which were generated from the MID data considering the observation weights given in the different MiD datasets (cf. Section 3.1.1) by use of the 'simPopulation' R package (Alfons and Kraft, 2017).

The empirical distributions of numerically dependent variables were estimated using *univariate Gaussian kernels* together with the observation weights given in the MiD datasets and a *univariate plug-in bandwidth selection* (Wand and Jones, 1994) by use of the 'ks' R package (Duong, 2017). An introduction to *kernel density estimation* is beyond the scope of this work but the interested reader can consult Härdle (2012, p. 549ff) for further information. Besides the procedure to rescale temporally dependent variables from individual minutes to five minute time steps mentioned in Section 3.1.3, this approach additionally allows for handling the uncertainty of the survey results, as the resulting empirical distributions are transformed from a discrete to a continuous scale, filling the gaps of unobserved but very likely variable values.

synPRO-emobility covers several behavioral aspects relevant for households' driving behavior as assessed in Chapter 3:

- *Number of available cars per household* dependent on socio-economic, sociodemographic and spatial household characteristics: household type (+++)[2], economic status (+++), place of residence (+)
- *Main user (vehicle) use frequency* dependent on socio-economic and sociodemographic household characteristics: household type (+), occupation of the primary driver (+)
- *Main user (daily vehicle) use probability* dependent on temporal aspects: main user (vehicle) use frequency (+), weekday (+)
- *Number of trips per (vehicle use) day* dependent on socio-economic, sociodemographic and temporal aspects: household type (+), occupation of the primary driver (+), vehicle use frequency of the primary driver (+), weekday of the vehicle use (+)
- *Departure and arrival places* dependent on socio-economic, sociodemographic and temporal aspects: trip index (+++), weekday (+), main user occupation (+)
- *Trip purposes* dependent on departure and arrival places (++)
- *Driven distance and driving time per <u>work</u> trip* dependent on socio-economic, sociodemographic and temporal aspects: main user occupation (+), weekday (+)
- *Driven distance and driving time per <u>non-work</u> trip* dependent on trip characteristics and temporal aspects: trip purpose (+++), trip distance category (+++), weekday (+)
- *First departure time per <u>work</u> trip* dependent on socio-economic, sociodemographic and temporal aspects: main user occupation (++), weekday (+)

[2] *large* (+++), *medium* (++) and *small* (+) effect size based on $||\bar{\delta}||_\infty$ or Cramer's V together with Cohen's effect size categories (cf. Section 3.3)

- *First departure time per <u>non-work</u> trip* dependent on socio-economic, sociodemographic and temporal aspects: trip purpose (+++), number of trips per use day (+++), weekday (+)

- *Parking time per <u>work</u> trip* dependent on socio-economic, sociodemographic and temporal aspects: main user occupation (+++), weekday (+)

- *Parking time per <u>non-work</u> trip* dependent on trip characteristic and temporal aspects: trip purpose (+++), weekday (+)

Note that the number of available BEVs per household (# BEV) is determined by the sampled number of ICEVs (# ICEV) together with a BEV market penetration rate $r_{BEV} \in [0, 1]$ and the following formula, assuming that BEV purchase decisions are equal amongst households for reasons of simplification[3]:

$$\# \text{ BEV} = \begin{cases} min(\lfloor(\# \text{ ICEV} \cdot r_{BEV}) + 0.5\rfloor, 1) & \text{for single person households} \\ min(\lfloor(\# \text{ ICEV} \cdot r_{BEV}) + 0.5\rfloor, 2) & \text{for two-person households} \\ \lfloor(\# \text{ ICEV} \cdot r_{BEV}) + 0.5\rfloor & \text{for multi-person households} \end{cases} \tag{4.1}$$

Also note that although Monday–Friday are denoted as 'workdays' throughout this work (cf. A.1.2), trips to of from the workplace (H-W, I-W, O-W, W-W) can also occur on Saturdays or Sundays for students and only on Saturdays for full-time and halftime occupied primary drivers as well as apprentices. Homemakers, pensioners or unemployed primary drivers are assumed to drive no trips departing from (or arriving at) the workplace. On workdays full-time and halftime occupied primary drivers are assumed to drive to the workplace on the first trip of the day and return home on the last one (cf. Figure 55–57 in A.5). Shopping trips can also occur on Sundays even though with a significantly reduced probability (cf. Figure 54 in A.5).

[3]cf. (Ensslen et al., 2015; Cervero, 1997) for more detailed information on EV purchase intentions of early adopters

Additionally the user can specify *holidays* and *vacation periods* for the desired simulation year. Holidays are regarded as Sundays in terms of driving behavior throughout the whole simulation. The defined vacation periods are randomly chosen and trimmed to a random number of days for each period. During vacation it is assumed that the households' BEVs are not used and parked at the arrival place of their last parking event.

Charging decision and technical parameters

The charging decision can be influenced by making use of four different parameters. The first, named *connection indifference level* in %-SOC, determines the battery's SOC upon arrival in percent at which the primary driver is indifferent between connecting and not connecting the BEV to a charging station. A second parameter, called *connection sensitivity* in %-SOC, determines the sensitivity for this connection decision. Further information on the modeling of this proceeding is given in Section 4.2.2. Third, the user can define the *minimum parking time for charging* in seconds that determines the smallest possible parking duration for a charging event independent from the parking location. Fourth, an integer defines the *charging energy strategy* determining how much energy is charged once the BEV is connected to the grid. So far, the model relies on the typical assumption that the maximum energy is charged within the available parking time. However, other strategies are conceivable such as limiting the charged energy to the required energy of the next trip (plus a certain buffer if applicable). Recent findings from Hahnel et al. (2013) show that EV users tend to predict their own driving behavior in terms of departure time and driving distance relatively well except for leisure trips.

Besides the behavioral parameters influencing the charging decision the model input comprises a couple of technical parameters: The parameter *BEV model number* specifies all technical aspects of the desired BEV such as the nominal consumption $c_{nominal}$ in kWh/100 km, the maximum reachable speed v_{max} in km/h, the nominal battery size $E_{nominal}$ in kWh, the effectively usable share of the battery ξ_{eff}, the effective range $r_{eff} = E_{nominal} \cdot \xi_{eff}$ in km and the available nominal charging power of the on-board integrated charging system of the vehicle $P^{BEV}_{nominal}$ in kW (Sakr et al., 2014). Table 9 shows an overview of the data acquired from *e-Stations: Elektroautos in der Übersicht* (2017) and used throughout synPRO-emobility on currently deployed BEV models in Germany. Note that ξ_{eff} was only specified for a few models so that all remaining were assumed to have an effectively usable share of 85 % based on the nominal battery size reported by the manufacturer. Also note that each BEV model was qualitatively assessed and assigned to one or several households' economic status. This allows for a plausible mix of BEV models regarding the desired household configurations set by the user in case the user specified a stochastic sampling of the BEV models beforehand.

Two parameters, the *average self-discharge rate of the first 24h* and the *average self-discharge rate of the following month*, both in %-SOC, determine the self-discharge behavior of each BEV's battery. The function was modeled having a non-linear part for the first 24 hours of self-discharging and a linear part for all subsequent self-discharging periods following the findings of (Spotnitz, 2003). Figure 34 shows an exemplary self-discharge curve parametrized with a 5 %-SOC average self-discharge rate both for the non-linear and the linear part of the function. More recently, self-discharging rates were specified with up to 5 %-SOC per month (Lu et al., 2013) so that the used parametrization is rather conservative especially if the battery is frequently operated between 100 and 95 %-SOC.

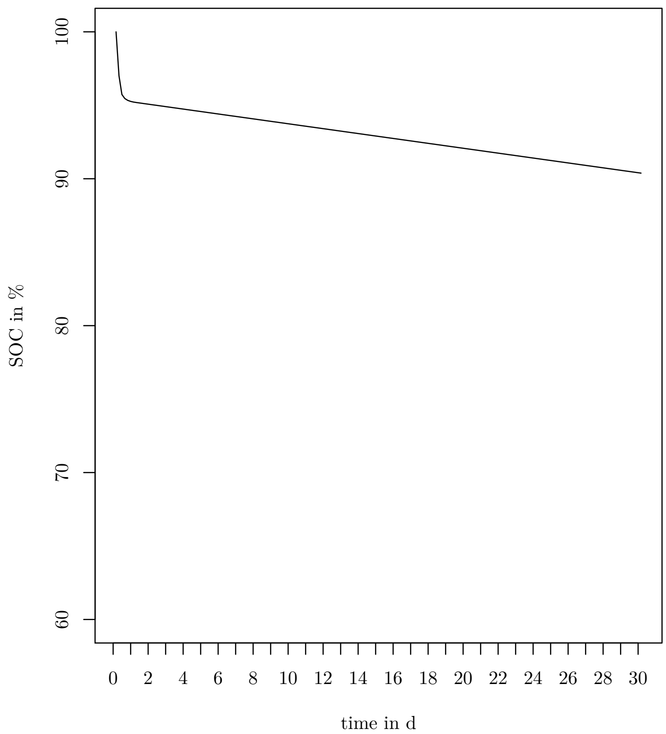


Figure 34: Exemplary Battery Self-discharge Curve for a Parking Duration of 30 Days

Three other technical parameters determine the shape of the active power charging curve (apcc) for the charging process at a specific charging station (EVSE) within the available parking time. First, the nominal charging power $P^{EVSE}_{nominal}$ in kW determines the overall level of the apcc. This parameter can be set deterministically using a certain value for each charging location in the model or stochastically. In the latter case a discrete *distribution* of $P^{EVSE}_{nominal}$ allows for the representation of differently equipped charging stations for each possible charging location in the model. Note that the sampling for the charging location at home or at the workplace is done once per simulation since both locations are considered to be unique so that their corresponding nominal charging power should not vary throughout the simulation. Also note that the final nominal charging power $P_{nominal}$ for the apcc is determined by the following formula

$$P_{nominal} = max(P^{BEV}_{nominal} \mid P^{BEV}_{nominal} \leq P^{EVSE}_{nominal}) \tag{4.2}$$

together with the following possible nominal power values for each charging location:

- 2.30 kW (10A, AC, single phase)
- 2.76 kW (12A, AC, single phase)
- 3.22 kW (14A, AC, single phase)
- 3.68 kW (16A, AC, single phase)
- 4.60 kW (20A , AC, single phase)
- 7.40 kW (32A, AC, single phase)
- 6.93 kW (10A, AC, three-phase)
- 11.09 kW (16A, AC, three-phase)
- 22.17 kW (32A, AC, three-phase)
- 43.65 kW (63A, AC, three-phase)
- 50.00 kW (DC)
- 120.00 kW (DC)
- 135.00 kW (DC)

The parameter *saturation charge level* in %-SOC specifies the constant-current-constant-voltage (CCCV) charging mode for each BEV's battery. Figure 35 shows an exemplary apcc at approximately 3.7 kW (230V, 16A, single-phase) with a saturation charge level of 90 %-SOC and a parking duration of 2 hours. One can see that 18 %-SOC of the overall energy is charged in constant current mode while the last 2 %-SOC are charged in constant voltage mode since the saturation charge level was exceeded after approximately 1.5 hours.

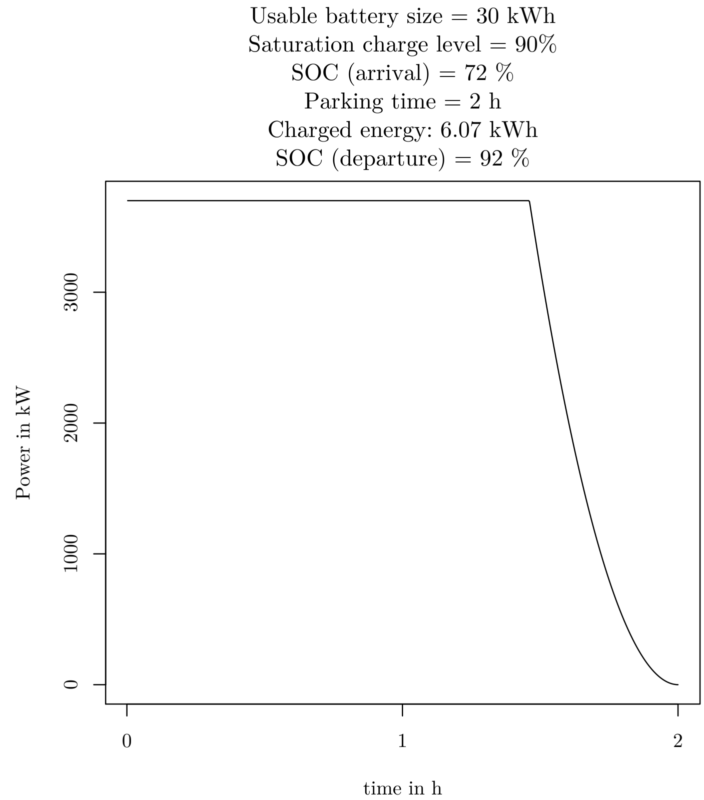


FIGURE 35: EXEMPLARY ACTIVE POWER CHARGING CURVE AT 3.7 kW FOR A PARKING DURATION OF 2 HOURS AND A SATURATION CHARGE LEVEL OF 90%

A last technical parameter, namely the *seasonal energy consumption scaling factor*, allows for a consideration of the energy consumption of different auxiliary devices with seasonal loads such as air-conditioning and heating of the passenger cell or cooling and heating of the vehicle's battery controlled by the battery management system (cf. Section 2.4). By default, the model assumes no seasonal scaling of $c_{nominal}$, though. A further extension to this approach could be the consideration of ambient temperatures by the use of test reference years already provided within the framework of synPRO for the thermal part of the model.

A final overview on all synPRO-emobility input parameters together with corresponding stochastic and temporal characteristics regarding the outcome of the simulation is given in Figure 36. Note that some parameters can be set for individual households or BEVs while others apply to all. Simultaneously, parameters can be specified as being stochastic (i.e. that the parameter value is determined during the simulation by means of unique or multiple sampling) or deterministic (i.e. that the parameter value is specified by the user prior to the simulation start). Furthermore, they can have a static (i.e. time-invariant) or dynamic (i.e. time-dependent) influence on the simulation.

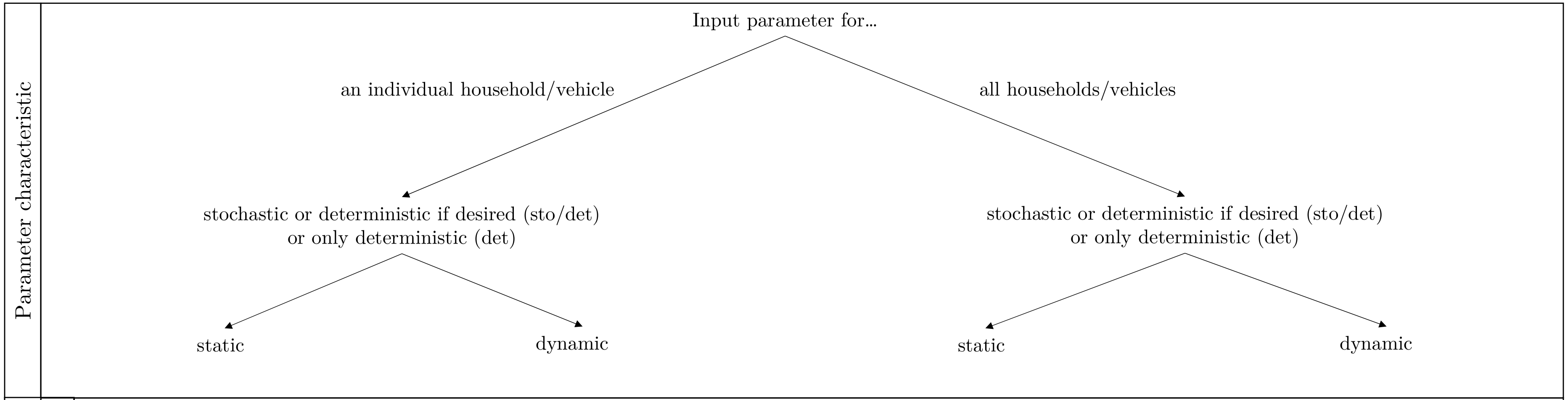
4.1.4 Output data

The model output are load profiles of BEVs charging with a minimum time resolution of 10 seconds for typical charging locations. The load profiles can be saved either aggregated for all BEV in the simulation, or individually.
In case a separate saving is used, every charging event of the load profile can be linked to a *trip information table* using a distinct key. This table provides further information for each trip such as the grid connection status after arrival, the start time step and the end time step of the charging and the charged energy. This is particularly useful for studying the optimization of the charging process, e.g. in terms of peak load shaving, charging cost minimization or optimizations regarding the provision of grid services. The latter especially benefits from the low minimum resolution of the model.

As supplemental information, a table is saved providing certain indicators for every simulated BEV such as the annual mileage, the total number of trips and charging events per year, the average driven distance per trip, the average SOC upon arrival and departure, the average charging duration, the annual charged and self-discharged energy based on the individual parking durations, the intermediate (fast-) charged energy for trips with insufficient range and the overall consumed energy of the BEV. Further information on the energy balance for consumed, charged, self-discharged and intermediate charged energy are given later in this chapter. These information can not only be used to verify the simulation results but also to provide expected values for key indicators of interest.

Table 9: Used Data on Currently Deployed BEV Models in Germany (*e-Stations: Elektroautos in der Übersicht*, 2017)

	Manu-facturer	**Model**	**Year**	$c_{nominal}$ **in kWh/ 100km**	v_{max} **in km/h**	$E_{nominal}$ **in kWh**	ξ_{eff}	r_{eff} **in km**	**Assigned to hh's economic status**	$P^{BEV}_{nominal}$ **in kW**
1	BMW	i3	2013	12.90	150.00	21.60	0.87	145.67	medium, high, very high	2.8, 3.6, 7.4, 50
2	BMW	i3	2015	12.60	150.00	33.20	0.82	216.06	medium, high, very high	2.8, 3.6, 7.4, 11, 50
3	Citroen	Berlingo L1	2014	17.70	110.00	22.50	0.85	108.05	very low, low, medium	2.8, 3.2, 50
4	Citroen	C-Zero	2010	12.60	130.00	14.50	0.85	97.82	very low, low, medium	2.3, 2.8, 50
5	Citroen	E-Mehari Cabrio	2016	15.00	110.00	30.00	0.85	170.00	low, medium	2.8, 3.6
6	Ford	Focus Electric	2012	15.30	137.00	23.00	0.85	127.78	medium	2.8, 3.6, 4.6
7	Hyundai	Ioniq Electric	2016	10.00	165.00	28.00	0.85	238.00	medium, high	6.6
8	Kia	Soul	2014	14.70	145.00	27.00	0.85	156.12	low, medium	2.8, 4.6, 6.6, 50, 63
9	Mercedes	B-Klasse Electric Drive	2013	16.60	160.00	28.00	0.85	143.37	medium, high	2.8, 3, 11
10	Mercedes	SLS AMG Electric Drive	2013	24.00	250.00	60.00	0.85	212.50	high, very high	2.8, 11, 22
11	Misubishi	i-MiEV	2010	13.50	130.00	16.00	0.85	100.74	very low, low, medium	2.3, 2.8, 50
12	Nissan	LEAF Tekna	2015	15.00	144.00	30.00	0.85	170.00	low, medium	2.8, 3.6, 6.6, 50
13	Nissan	LEAF Tekna	2013	15.00	144.00	24.00	0.85	136.00	low, medium	2.8, 3.6, 6.6, 50
14	Nissan	LEAF Acenta	2013	15.00	144.00	24.00	0.85	136.00	low, medium	2.8, 3.6, 6.6, 50
15	Nissan	LEAF Visia	2013	15.00	144.00	24.00	0.85	136.00	low, medium	2.8, 3.6, 6.6, 50
16	Opel	Ampera-E	2017	12.00	145.00	60.00	0.85	425.00	medium, high	2.8, 3.6, 50
17	Peugeot	iOn	2010	13.50	130.00	16.00	0.85	100.74	very low, low, medium	2.3, 2.8, 50
18	Peugeot	Partner L1	2014	17.70	110.00	22.50	0.85	108.05	very low, low, medium	2.8, 3.2, 50
19	Renault	Kangoo Z.E. Maxi	2012	15.50	130.00	22.00	0.85	120.65	very low, low, medium	2.8, 3.2, 50
20	Renault	Kangoo Z.E.	2012	15.50	130.00	22.00	0.85	120.65	very low, low, medium	2.8, 3.2, 50
21	Renault	Twizy Cargo life	2013	6.00	80.00	8.00	0.85	113.33	medium, high, very high	2.8, 3.6
22	Renault	Twizy Urban	2011	6.00	80.00	8.00	0.85	113.33	medium, high, very high	2.8, 3.6
23	Renault	ZOE R400 Life	2016	13.30	135.00	41.00	0.85	262.03	low, medium	2.8, 3.6, 11, 22
24	Renault	ZOE R240 Life	2015	13.30	135.00	25.93	0.85	165.72	low, medium	2.8, 3.6, 11, 22
25	Smart	fortwo Coupé	2012	14.30	125.00	17.60	0.85	104.62	medium, high, very high	2.8, 3.3, 22
26	Smart	fortwo Caprio	2012	14.30	125.00	17.60	0.85	104.62	medium, high, very high	2.8, 3.3, 22
27	Tesla	Model S 75	2015	17.90	225.00	75.00	0.85	356.15	very high	2.8, 11, 120
28	Tesla	Model S 75D	2015	17.00	225.00	75.00	0.85	375.00	very high	2.8, 11, 120
29	Tesla	Model S P100D	2016	16.30	250.00	100.00	0.85	521.47	very high	2.8, 11, 22, 120
30	Tesla	Model S 60	2012	18.10	210.00	60.00	0.85	281.77	very high	2.8, 7.4, 11, 22, 135
31	Tesla	Model X 90D	2015	18.40	250.00	90.00	0.85	415.76	nvery high	2.8, 11, 22, 120
32	Tesla	Model X P100D	2015	18.45	250.00	100.00	0.85	460.70	very high	2.8, 11, 22, 120
33	VW	e-Golf	2014	12.70	140.00	24.20	0.85	161.97	medium, high, very high	2.8, 3.6, 40
34	VW	e-Golf	2016	12.00	150.00	35.80	0.85	253.58	medium, high, very high	2.8, 7.2, 40
35	VW	e-Up!	2014	11.70	130.00	18.70	0.85	135.85	medium, high, very high	2.3, 2.8, 3.6, 40
36	VW	e-Up!	2012	12.00	130.00	18.70	0.85	132.46	medium, high, very high	2.3, 2.8, 3.6, 40



Parameters	an individual household/vehicle: static	an individual household/vehicle: dynamic	all households/vehicles: static	all households/vehicles: dynamic
Households	– Household type (sto/det) – Economic household status (sto/det) – Place of residence (s/d) – Number of available BEV (sto/det)		– BEV market penetration rate in % (d)	
Electric Vehicles	– Main user occupation (sto/det) – Main user (vehicle) use frequency (sto/det) – BEV model number (sto/det) Connection sensitivity in %-SOC (det) – Charging energy strategy (det)	– $P^{EVSE}_{nominal}$ in kW dependent on the charging location at time t (sto/det) – Connection indifference level in %-SOC dependent on the charging location at time t (det)	– Minimum parking time for charging in s (det) – Saturation charge level in %-SOC (det) – Average self-discharge rate of the first 24 h in %-SOC/d (det) – Average self-discharge rate for the following months in %-SOC/m (det)	– Vacation periods (sto) – Holidays (det) – Seasonal energy consumption scaling factor for spring, summer, fall, winter (det) – Distribution of $P^{EVSE}_{nominal}$ dependent on the charging location at time t (sto/det)

Figure 36: Overview of Input Parameters Categorized by Stochastic and Temporal Characteristics Regarding Their Influence on the Simulation

4.2 From data to BEV charging profiles

Four central questions need to be answered to be able to generate an electric load profile and evaluate potential flexibility of BEV charging:

1. When and where is the vehicle arriving?
2. What is the SOC of the battery when arriving at a charging station?
3. Is the vehicle user willing to charge?
4. What is the SOC of the battery when leaving?

Question 1 relates to the generation of driving profiles which is described in the following subsection. Questions 2–4 relate to the representation of charging locations and decisions in the model, which will be described in the second subsection of this chapter.

4.2.1 Generation of driving profiles

Once the number of available BEVs per household given a specific market penetration rate (cf. Equation 4.1), a certain occupation type and a corresponding vehicle use frequency is sampled or assigned (if predefined) to each BEV's primary driver. Additionally, a BEV model together with its technical properties is sampled (if not given). Subsequently the following processing steps are performed by the model:

1. In a first step the daily use or disuse of a particular BEV (and corresponding primary driver) is sampled for all days of a year considering holidays (seen as Sundays) as well as vacation periods (seen as *disuse* days) dependent on the particular weekdays and the previously sampled vehicle use frequency. (*Note that this procedure assumes that the use or disuse of the vehicle on a particular day is stochastically independent from the use or disuse on the day before, resulting from the fact that the data at hand provided only information for single days.*)
2. Next, the total number of trips per day N is sampled for all use days of a year based on the particular weekday, the priorly sampled vehicle use frequency of the primary driver, his main user occupation and the type of his household. (*Note again, that this procedure assumes that the number of trips on a particular vehicle use day is stochastically independent from the use or disuse and the number of trips driven on*

the day before resulting from the fact that the data at hand provided only information for single days.)

3. Subsequently, an inhomogeneous first-order Markov chain constructs a logically consistent sequence of departure and arrival places for all trips based on the parking locations defined in Section 3.1.3 and dependent on the the trip index, the particular weekday and the occupation of the primary driver. (*Note that this procedure assumes that the driving behavior regarding the current departure and arrival place X_n is only dependent on the departure and arrival place of the prior trip X_{n-1}, i.e. the first-order Markov property $P(X_n = x_n \mid X_{n-1} = x_{n-1}, \ldots, X_0 = x_0) = P(X_n = x_n \mid X_{n-1} = x_{n-1})$ holds for all possible trips $n = 1, \ldots, \sum_{d}^{365} N_d$ of a year. However, most temporal in-day regularities resulted from patterns for the first and the last trip per day, as Figure 29 indicates, and are therefore considered by the above proceeding.*) It is worth noting again, that it is assumed that trips to or from the workplace (H-W, I-W, O-W, W-W) can also occur on Saturdays or Sundays for students and only on Saturdays for full-time and halftime occupied primary drivers as well as apprentices. Homemakers, pensioners or unemployed primary drivers are assumed to drive no trips departing from (or arriving at) the workplace. On workdays full-time and halftime occupied primary drivers are assumed to drive to the workplace on the first trip of the day and return home on the last one (cf. Figure 55–57 in A.5).

4. A search algorithm marks all equal trips per day based on logical reasoning on parking place sequences using the fact that the parking places H and W are seen as mutually exclusive throughout this work: for example, the sequence (H, W, I, O, H) would be marked as (1, 2, 3, 4) whereas this sequence (H, W, H, I, H, O, H, O, H) would be marked as (1, 1, 2, 2, 3, 3, 4, 4) granting information on trips that should receive equal driven distances since the vehicle is moved back and forth between unique parking places. (*Note that this procedure assumes that people tend to drive the same ways when driving back and forth between these parking places.*)

5. Next, the sampled sequence of departure and arrival places is used to assign a trip distance category (cf. Section 3.1.3) and a sampled trip purpose to every trip using the information on trip equality from the previous step. (*Note that this procedure does consider the in-day time dependency of trip purposes indirectly since the departure and arrival places are correspondingly controlled by the trip index.*

However, this does not fully prevent rather implausible cases such as shopping trips in the late evening.)

6. The driven distance from home to work (or reversed) is sampled once for the whole simulation year dependent on the sampled main user occupation (if 'fulltime', 'halftime', 'apprentice' or 'student') and is assigned to all corresponding trips using the information on equal trips from Step 5. (*Note that it is assumed that people always want to reach the same workplace or the same home respectively. Additionally, the maximum driven distance from home to work (or reversed) is limited by the effective range of the BEV model* r_{eff}.)

7. The driven distance of all other combinations of departure and arrival places is sampled iteratively for each trip dependent on the trip distance category, the trip purpose, and the particular weekday and is assigned to to all corresponding trips using the information on equal trips from step 5. (*Note that this procedure, for example, allows for leisure trips having a longer driven distance on the weekend than on workdays. Trips having a driven distance lager than the currently effective range of the BEV are assumed to be covered by intermediate (fast-) charging. The resulting SOC upon arrival is assumed to be zero, cf. Step 15.*)

8. The time of the first departure from home to work is sampled dependent on the particular weekday and the previously sampled main user occupation (if 'fulltime', 'halftime', 'apprentice' or 'student').

9. The time of the first departure of all other combinations of departure and arrival places is sampled dependent on the trip purpose, the overall number of trips driven on the particular day and the weekday. (*Note that this procedure allows for an earlier departure if a lot of subsequent trips are planned. However, this does not account for days on which the first trip is a trip from home to work.*)

10. The driving time from home to work (or reversed) is sampled dependent on the sampled main user occupation (if 'fulltime', 'halftime', 'apprentice' or 'student'), the particular weekday and the sampled driven distance from step 6 using a loop to determine a plausible average speed limited by the maximum speed v_{max} of the particular BEV model. The quantity is assigned to the corresponding trips using the information on equal trips from step 5. (*Note that this procedure assumes that*

trips from work to home (or reversed) usually have the same driving time and are not influenced by detours or a higher volume of traffic.)

11. Rejection sampling for each day:

    (a) The driving time of all other combinations of departure and arrival places is sampled iteratively for each trip dependent on the trip purpose, the trip distance category, the particular weekday and the sampled driven distance from step 6 using a loop to determine a plausible average speed limited by the maximum speed v_{max} of the particular BEV model. The quantity is assigned to the corresponding trips using the information on equal trips from step 5. (*Note that this procedure assumes that trips being driven back and forth regarding the unique parking places H or W usually have the same driving time and are not influenced by detours or a higher volume of traffic.*)

    (b) The parking time at work is sampled iteratively for each trip dependent on the sampled main user occupation (if 'fulltime', 'halftime', 'apprentice' or 'student') and the particular weekday. The quantity is assigned to all corresponding trips. (*Note that this procedure allows for a different parking duration at work on weekends compared to workdays.*)

    (c) Calculate the last arrival time of the day $t_N^{arrival}$ by summing up the first departure time and all subsequent driving and parking times of the particular day. If the last arrival time of the day is $\geq 28h$ (04:00 a.m. of the following day) go back to the beginning of Step 11, otherwise continue with Step 12.

12. Calculate the departure and arrival time for each trip using a running total of the first departure time and all subsequent driving and parking times for each day of the year.

13. Calculate the last parking time of the day $t_N^{parking}$ for each trip by determining the total number of following disuse days D^{disuse} and the departure time of the next use day $t_1^{departure}$ together with the following formula: $t_N^{parking} = 24 - t_N^{arrival} + (24 \cdot D^{disuse}) + t_1^{departure}$

4.2.2 Representation of charging decisions, stations and quantities

As soon as the arrival times for each parking location are determined Question 2, 3 and 4 arise:

14. The nominal charging power of the charging station at home $P^{EVSE-H}_{nominal}$ and at work $P^{EVSE-W}_{nominal}$ are sampled once for the whole simulation year based on the respective distributional parametrization provided as model input (cf. Section 4.1.3).

15. Determine charging decision upon arrival for each parking event:

    (a) Calculate the current range r_n of the BEV based on the last SOC upon departure $SOC^{departure}_{n-1}$ (starting with a fully charged battery on the 1st of January).

    (b) If r_n is larger than the currently driven distance l_n continue with (c), else, assume intermediate (fast-) charging:

        i. Calculate the intermediate charged energy E_{imc} based on the consumption of the particular BEV model: $E_{imc} = (l_n - r_n) \cdot c_{nominal}/100$

        ii. Set $SOC^{arrival}_{n} = 0$ and set the grid connection status upon arrival to 'connected'.

    (c) Calculate the current SOC upon arrival $SOC^{arrival}_{n}$ based on the last SOC upon departure $SOC^{departure}_{n-1}$ (starting with a fully charged battery on the 1st of January) and the total consumed energy $E_{con} = l_n \cdot c_{nominal}/100$: $SOC^{arrival}_{n} = SOC^{departure}_{n-1} - ((E_{con} \cdot 100)/(E_{nominal} \cdot \xi_{eff}))$

    (d) If the current parking time $t^{parking}_{n}$ is smaller than the *minimum parking time for charging* (cf. Section 4.1.3) continue with the next parking event starting from Step 15 (a), else:

        i. Determine the probability for connecting the BEV to a charging station dependent on the current parking location, the current trip purpose and the current SOC upon arrival using an univariate *logit* model parametrized with the *connection indifference level* and the *connection SOC-sensitivity* level (cf. Section 4.1.3). Besides connecting the BEV to a charging station at home (EVSE-H) or at work (EVSE-W), a charging station at a place of purchase inside or outside the primary driver's own city or town (EVSE-POP-IC, EVSE-POP-OC) for the trip purpose 'shopping' or somewhere else inside or outside the primary driver's own city or town (EVSE-SWE-IC, EVSE-SWE-OC) for all other trip purposes is assumed (cf. Section 2.4) (*For further information see paragraph 'Modeling the connection probability' below.*)

ii. Sample the grid connection status based on the determined distribution for connecting the BEV to the current charging station $P(\text{'connected'}) \Rightarrow P(\text{'not connected'}) = 1 - P(\text{'connected'})$.

(e) If the grid connection status is 'not connected', continue with Step 15 (f), else:

i. If the current parking place is H or W, continue with (e) ii., else, sample $P_{nominal}^{EVSE-POP}$ or $P_{nominal}^{EVSE-SWE}$.

ii. Determine the desired SOC upon departure for the next trip $SOC_{n+1}^{departure}$ dependent on the *charging energy strategy* and calculate the resulting apcc together with the charging duration $t_n^{parking}$ and the total charged energy E_{ch} using the final nominal charging power $P_{nominal}$ together with the *saturation charge level* for $t_n^{parking}$ (cf. Figure 35 in Section 4.1.3). (*Note that this procedure allows for an interruption of the charging process as further charging is postponed to a future charging event in case the particular parking time is not sufficient.*)

(f) Calculate the self-discharged energy E_{sdc} dependent on $SOC_n^{arrival}$ and $t_n^{parking}$ (if there was no charging event) and dependent on $SOC_{n+1}^{departure}$ and $t_n^{charging}$ (if there was a charging event) together with the *average self-discharge rate of first 24 h in %-SOC/d* and the *average self-discharge rate for following months in %-SOC/m*.

Energy balance for the BEV's battery

Having introduced all forms of energy gains and losses of the BEV's battery, one can set up the total energy balance for the proposed model:

$$E_{ch} + E_{imc} = E_{con} + E_{sdc} + \epsilon \tag{4.3}$$

with E_{ch}, being the total charged energy at the 6 possible charging stations in the model, E_{imc}, being the intermediate charged energy for trips with insufficient range, E_{con}, being the kinetic energy to move the vehicle together with the energy consumption of all auxiliary devices such as air-conditioning/heating of the passenger cell and cooling/heating of the battery, and E_{sdc} being the self-discharged energy for the total parking time over the year. The error term ϵ is incorporated due to computational reasons regarding the averaging of charging power upon discrete time slots in order to allow for temporal output resolutions of the apcc beyond the native resolution of 10 seconds. It is usually $\pm 0.1 - 0.2$ % of the total annually charged energy for an output resolution of 60 s.

After having presented the representation of different charging locations in the model related to the first part of research question II the following paragraph gives detailed information on the modeling of the connection decision answering the second part of research question II:

Modeling the connection decision

The *logistic regression*, also often called *logit model*, is a widely acknowledged type of statistical model to represent discrete decision behavior where the dependent variable is categorical and the independent variables (regressors) can have any level of measurement. If there are only two decision options (categories) these models are called *binomial* or *binary logistic regression* in contrast to the *multinomial logistic regression* where multiple categories are available. If there is only one predictor explaining the categorically dependent variable, one speaks of a *univariate* logit model, or else of a *multivariate* logit model (Hilbe, 2009).

The dependent variable in a binomial logistic regression model (univariate or multivariate) is usually dummy coded. It can therefore ideally be used to model 'yes/no' decisions, such as the decision regarding 'charing' ($Y = 1$) versus 'no charging' ($Y = 0$) relevant to this work.

Franke and Krems (2013) found out that BEV charging can be explained to a large extent by a "comfortable range" and a "user-battery-interaction style" (UBIS), which is a certain score index of survey-assessed aspects regarding the BEV user's battery interaction. Concerning the initial SOC upon recharging, a hypothesis of the charging behavior related to that of mobile phones (Rahmati and Zhong, 2009) could also be confirmed for BEV drivers, so that the distribution of an initial battery's SOC upon recharging is more uniform for users with a lower UBIS and more normal (i.e. distinct peak, narrower) for users with a higher UBIS. Following these findings and for reasons of unavailable charging data to fit a logit model, the independent variable used throughout this work is only the battery's SOC. This quantity can be calibrated with empirical findings on the initial SOC upon recharging from Schäuble et al. (2017*b*) (cf. Section 4.3). Note that this approach assumes that primary drivers in the model have a very high UBIS, so that they all react rather sensitively to a certain SOC threshold and that main users of a BEV with a larger battery capacity tend to recharge at the same threshold as main users with a smaller battery capacity.

Assuming an SOC-dependent recharge behavior, the logit model therefore becomes univariate. The cumulative distribution function (CDF) of the univariate logit model for a random variable X is:

$$F(x, \mu, s) = \frac{1}{1 + (\exp^{-\frac{x-\mu}{s}})} = \frac{1}{2} + \frac{1}{2}\tanh\frac{x-\mu}{2s} \tag{4.4}$$

with x being a realization of the random variable X, μ being the expected value of the distribution and s being a scaling parameter, which is proportional to the standard deviation $\sigma = \frac{s \cdot \pi}{\sqrt{3}}$ of the distribution. The parameter s with respect to a known standard deviation σ is therefore:

$$s = \frac{\sigma \cdot \sqrt{3}}{\pi} \tag{4.5}$$

The parameter μ can be seen as a *connection indifference level* in %-SOC since the CDF always reaches an exact probability of 0.5 at this point. Similarly, the parameter s can be interpreted as a *connection sensitivity* in %-SOC, since it determines the width of the SOC-range where the primary driver's probability to connect the vehicle to a charging station is increasing with regard to further reductions of the SOC.

Figure 37 and 38 show the CDF (mirrored along the y-axis) of connecting the vehicle to a charging station for a lower and a higher connection sensitivity and different indifference levels. Note that if $\mu = 0$ the vehicle is certainly not connected. If $\mu = 100$ the vehicle is certainly connected.

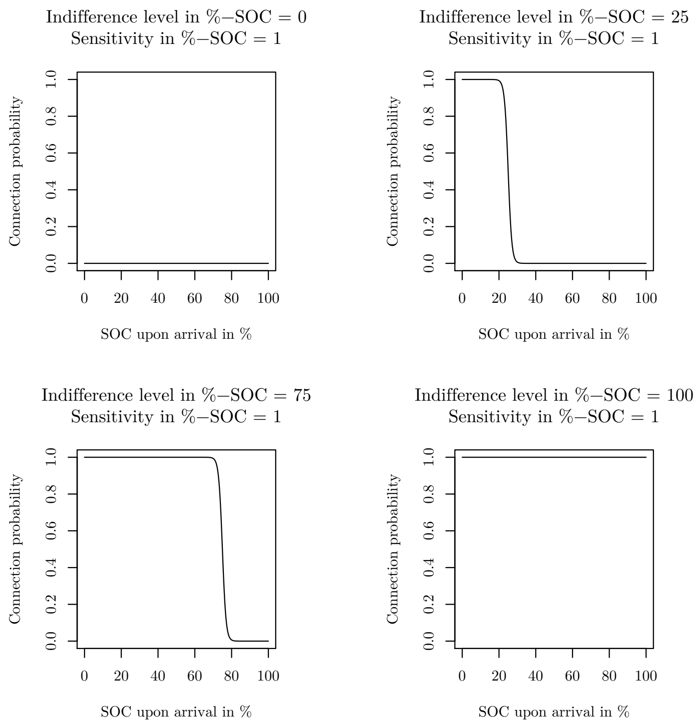


Figure 37: Connection probability based on a univariate logit model dependent on the battery's SOC upon arrival together with a lower connection sensitivity

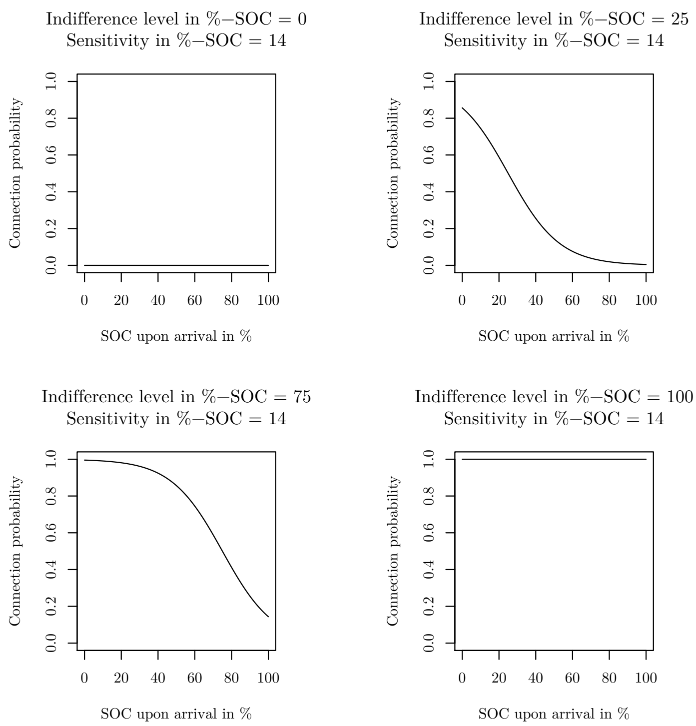


Figure 38: Connection probability based on a univariate logit model dependent on the battery's SOC upon arrival together with a higher connection sensitivity

Expressed in therms of probability theory, one would in fact define the following condition for the *connection indifference level*

$$P(Y = 1 \mid SOC_{arrival}) = 0.5 \tag{4.6}$$

so that that the primary driver has the same probability for connecting the BEV to a charging station than not doing so based on the particular SOC upon arrival. Analogously, a lower (higher) SOC would have a higher (lower) probability for connecting the vehicle to a charging station. The *connection sensitivity* defines the extent in %-SOC to which the primary driver starts to have an increasing probability to connect the BEV to a charging station.

As mentioned before, the described modeling approach using the battery's SOC upon arrival for individual charging locations (with possibly different charging powers) under consideration of a minimum parking time is not the only possible influencing factor on the probability to connect the vehicle to a charging stations: other aspects such as the 'comfortable range', the charging price, the accessibility of other charging stations in terms of time and distance, the practicability of the connection at a certain charging station as well as security and safety considerations in terms of charging gear and with respect to the charging location's surrounding could play an important role. Therefore, the proposed approach does not capture all influencing factors that may determine a charging decision. Future modeling attempts could rely on *multivariate logit models* to capture further key factors.

4.3 Validation and exemplary results

In order to validate the model, a stepwise calibration and comparison strategy is pursued: first, the *connection indifference level* for the four different charging location types (H, W, POP, SWE) is calibrated using empirical findings from Schäuble et al. (2017*b*) regarding the distribution of the initial battery's SOC upon recharging, independent from the charging location while simultaneously considering charging location preferences observed in different field trials around the world (Morrissey et al., 2016; Franke and Krems, 2013; Jabeen et al., 2013; Speidel et al., 2012). Second, indicators calculated from the simulation results, such as the total number of charging events per vehicle and per day as well as the charged energy per vehicle and per day, are compared to empirical findings of four different field trials in Germany.

1. *MINI E field trial, Germany*
2. *Cross border mobility for electric vehicles (CROME)*
3. *Intelligent Zero Emission Urban System (iZEUS)*
4. *Operator model for electric fleets in Stuttgart (Get eReady)*

The shape of the average load profile simulated with synPRO-emobility is also compared to the synthetic average load profile of Schäuble et al. (2017*a*) which is based upon empirical charging data gathered in three of the four before mentioned fleet trials (field trial 2, 3 and 4). In case of deviations, possible reasons are discussed and the *connection indifference level* is adapted accordingly.

Note that the validation procedure described above was chosen since representative empirical charging data, for example, to fit a connection decision model, such as the univariate logit model presented in Section 4.2, and to quantitatively assess deviations of the simulated average profiles from real average charging profiles, were unavailable in the context of this work. However, the proposed procedure allows for a quantitative examination of the results regarding empirical indicators and a qualitative comparison of the shape of the average synthetic load profile simulated with synPRO-emobility to the average synthetic load profile simulated by Schäuble et al. (2017*b*).

Table 10 gives an overview of the available information on all four field trials regarding the participants, their characteristics, the deployed EV models, the reported average values

Table 10: Overview of four extensive EV field trials in Germany based on (Schäuble et al., 2017*b*; Schäuble et al., 2016; Ensslen et al., 2016; Franke and Krems, 2013; Neumann et al., 2010)

Field trial name	**Year**	**Region**	**Participants**	**Participants' characteristics**	**Deployed EV models**	**Miscellaneous**	**Average vehicles' charging per day**	**Average vehicle's charged energy per day**
MINI E field trial, Germany	2010 – 2011	Berlin and surroundings	40 private households (31 hybrid household, 9 EV households)	75% university degree, 82.5% male drivers, 75% no EV experience, 43% family households, willingness to pay a montly leasing rate, available garaging with suitable connection for power supply	40 MINI Cooper E with 250 km range	recharging at a wallbox installed at home or at one of the public charging stations spread over the city of Berlin	0.4	n/a
Cross border mobility for electric vehicles (CROME)	2011 – 2013	Southwest Germany & Eastern France	EV fleets from German and French companies ($\geq$ 100 EVs)	(Schäuble et al., 2016)	53 Smart fortwo electric drive phase two, 7 Renault Kangoo Z.E., 11 Peugeot iOn, 2 Porsche Boxster e, 3 Porche Panamera S Hybrid, 4 Toyota Prius Hybrid, and other	EVs equipped with on-board data loggers and smart-phones with GPS-tracking, EV were used by multiple users, 3160 valid charging events	1.71^a	4.34^a kWh
Intelligent Zero Emission Urban System (iZEUS)	2012 – 2014	Southwest Germany	50 private households	n/a	50 Smart fortwo electric drive phase three, 5 Toyota Prius, 1 Opel Ampera, and other such as Mercedes-Benz Vito E-cell	EVs equipped with on-board data loggers and tablets with GPS-tracking, 6088 valid charging events	n/a	n/a
Operator model for electric fleets in Stuttgart (Get eReady)	2013 – 2015	Stuttgart and surroundings	82 small and medium-sized companies, 27 others, (327 EVs and 344 distinct EV drivers)	up to 250 employees, 36% from the manufacturing sector	21 different EV models	local charging network with 181 charging points, compensation for participation, on average 16 months of participation, 19696 valid charging events	1.29^a	10.04^a kWh

[a] average regarding days on which the vehicle was charged

of the vehicles' charging and charged energy per day and other background information. It is important to note here that the specifications for the field trials 2, 3, and 4, regarding average quantities per vehicle and day, refer to days on which the vehicle was charged and not to days on which the vehicle was present in the field trial (cf. corresponding footnote of Table 10). However, Schäuble et al. (2017*b*, p. 256f) report the average vehicles' charging events per day (regarding the days on which the vehicle was present in the field trial) over all three field trials at 0.2857, so that an average vehicle in all three field trials was charged on average every third to fourth day. The weekly distribution is: Mon (0.35), Tue, Wed, Thu (0.37), Fri (0.34), Sat (0.11) and Sun (0.08) (cf. the percentage share over all three field trials in Figure 39).

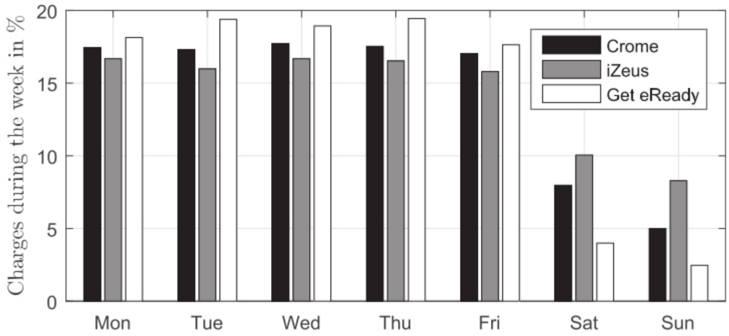


Figure 39: Percentage of Charging Events per Weekdays (Schäuble et al., 2017*b*, p. 256)

The four field trials were conducted between 2010 and 2015 in different regions of Germany. Two field trials, the *MINI E field trial* and the *Get eReady* field trial aimed at large cities (Berlin and Stuttgart) and a rather local charging network within the trial (home charging and charging points spread over the urban areas). The latter, providing the majority of valid charging operations (67%) for the empirical data base of Schäuble et al. (2017*b*), mainly focused on fleets of small and medium-sized companies (n = 82) with 327 vehicles of 21 different EV models and 344 distinct EV drivers in total, while the former was targeted at private households (n = 40). The *CROME* field trial focused on a rather regional area located in the border region of Southwest Germany and Eastern France with over 100 EVs of different company fleets. The *iZeus* field trial focused on private households (n = 50) instead. Regarding the deployed EV models in the field trials, participants in the *MINI E field trial* used an EV with a rather large range of 250 km whereas the *CROME* and the *iZeus* field trials were dominated by EV models with a smaller range, such as 150 km of the Smart fortwo electric drive phase three. Detailed information on the deployed EV models in the *Get eReady* field trial were not available.

All simulations in synpRO-emobility were performed for the simulation year 2017 with the following parameterization except for the *connection indifference level* (if not stated differently) in order to ensure a comparability to the Scenario 'P0' of Schäuble et al. (2017*b*, p. 13) that relates to a low market share of fast charging at home, at work or at public charging stations and a high market share of fast charging stations at semi-public places such as supermarkets or parking sites:

- Quantity (100)
- Household type (sampling[4])
- Economic household status (sampling)
- Place of residence (sampling)
- Number of available BEVs per household (1)
- BEV market penetration rate (50%[5])
- Main user occupation (sampling)
- Main user (vehicle) use frequency (sampling)
- BEV model number (sampling)
- Connection sensitivity in %-SOC (7.82)
- Charging energy strategy (1 = maximum charging)
- $P_{nominal}^{EVSE-H}$ (sampling)
- $P_{nominal}^{EVSE-W}$ (sampling)
- $P_{nominal}^{EVSE-POP}$ (sampling)
- $P_{nominal}^{EVSE-SWE}$ (sampling)
- Minimum parking time for charging in s (600 = 10 min)
- Saturation charge level in %-SOC (90)
- Average self-discharge rate of the first 24 h in %-SOC/d (5)
- Average self-discharge rate of the following months in %-SOC/m (5)
- Vacation periods (none)
- Holidays (Germany, Baden-Württemberg, 2017)
- Seasonal energy consumption scaling factor for spring, summer, fall, winter (1, 1, 1, 1)

[4] Instead of providing a particular value the model samples variable value from the corresponding empirical distribution of the input data (cf. Section 4.1.3

[5] Note that the market penetration rate is not affecting the simulation since a deterministic value is provided for the number of available BEVs per household

- Distribution of $P_{nominal}^{EVSE-H}$ $(P(3.7kW) = 1)$
- Distribution of $P_{nominal}^{EVSE-W}$ $(P(3.7kW) = 1)$
- Distribution of $P_{nominal}^{EVSE-POP}$ $(P(22kW) = 0.94,\ P(50kW) = 0.06)$
- Distribution of $P_{nominal}^{EVSE-SWE}$ $(P(3.7kW) = 0.9,\ P(22kW) = 0.1)$

A typical simulation run with these settings computing and saving both the aggregated and the single load profiles per BEV took 50 minutes on a Linux machine with an Intel i7 processor with 4 cores (8 threads) and 16 GB of RAM and a HDD. Note that the saving of single load profiles with a high resolution can take significantly more time on a HDD compared to a SSD.
Note that the connection sensitivity s was calculated using Equation 4.5 together with the reported standard deviation of the initial battery's SOC upon recharging between 6 a.m. to midnight $\sigma(SOC_{init}) = 14.2$ %-SOC of Schäuble et al. (2017*b*, p. 257): $s = \sigma(SOC_{init}) \cdot \sqrt{3}/\pi = 7.82$ %-SOC. The distributions of $P_{nominal}^{EVSE}$ for the respective charging stations were adopted from the corresponding 'P0' scenario of Schäuble et al. (2017*b*, p. 263).

The *connection indifference levels* for the charging stations at home (EVSE-H) is firstly set to 80%-SOC since several field trials reported home-charging to be the most preferred option. This value is approximately the daily average of the third quartile $\bar{q}_{0.75} \approx 80$ %-SOC of the distribution of the battery's SOC upon recharging from the data basis of Schäuble et al. (2017*b*) (cf. Figure 40).

A field trial conducted in Western Australia in the city of Perth from 2012 to 2013 with 11 converted Ford Focus as company fleet vehicles (with approximately 130 km of range) indicates a similar recharge behavior, in that Azadfar et al. (2015, p. 1074f) states that "drivers frequently charged their vehicle before reaching the battery expected range [...] maintaining a relatively high battery state of charge". However, regarding the average frequency of charging events per vehicle and per day driven, the results differ significantly from those of Schäuble et al. (2017*b*), since more than 60% of the charging events occurred on days with more than 5 charging events per vehicle and day driven. Speidel et al. (2012, p. 5f) provide a possible limitation for this statistic: several vehicles were shared pool vehicles within the company fleet and did not have a dedicated driver so that they might be recharged frequently due to courtesy before being handed over to the next driver.

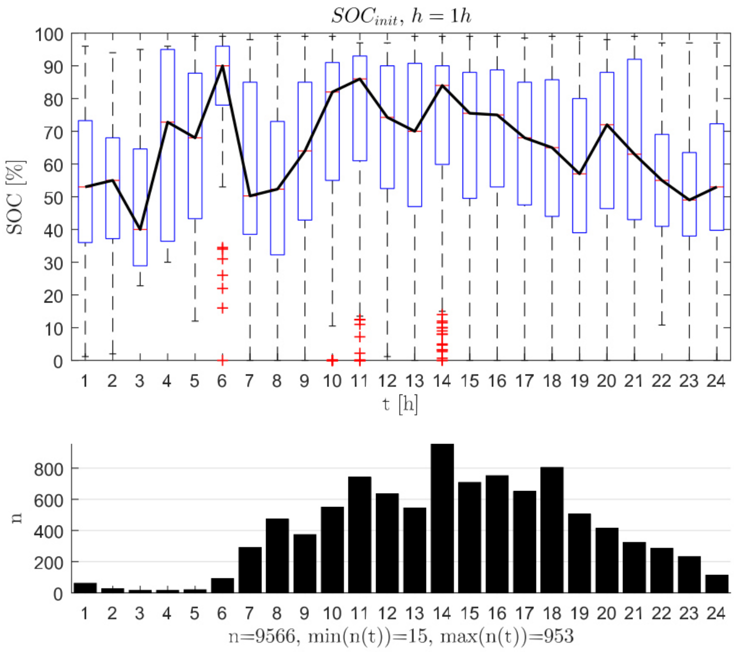


FIGURE 40: HOURLY DISTRIBUTION OF THE BATTERY'S SOC UPON RECHARGING (BOX PLOT) AND THE CORRESPONDING NUMBER OF CHARGING EVENTS (HISTOGRAM) (SCHÄUBLE ET AL., 2017*b*, P. 257)

Concerning the preference between charging at home and at work the only finding in the literature examined in the context of this work also relates to the field trial in Perth: EVs were recharged with a probability of 29% when parked at home, with 63% when parked at work or at various business locations, with 86% when parked at charging stations and only with 4% when parked at unknown locations. Again this result might be heavily biased by the limitations to the field trial since some organizations had restrictions on the vehicle use, such as not taking the vehicle home, or that the EV drivers were not reimbursed for electricity usage in their home or because of installed charging stations at the premises of four organizations specifically for the fleet's EVs. For that reason, the same *connection indifference level* of 80%-SOC is firstly assumed for the charging stations at work (EVSE-W) for the simulation in synPRO-emobility.

Regarding the preference between charging at home or work (private charging stations) and semi-public (e.g. at supermarkets, car parks, petrol stations) or public charging stations (e.g. at the curbside), several studies reported similar tendencies: for example, during the *MINI E field trial* users most often employed private charging stations (83.7% of all charging events) and only seldomly public charging stations (4.8%) and normal sockets (11.5%) (Franke and Krems, 2013, p. 81f). A recent study on charging behavior of EV drivers for the entire island of Ireland confirms these results with respect to the charging power saying that even though the EV users' preferred charging location was at home (with a large proportion in the evening), fast-charging locations in particular at car park locations were seen to be favored by EV users over other charging locations without fast-charging (e.g. on-street charging) (Morrissey et al., 2016, p. 269f). To incorporate these preferences into the model, the *connection indifference level* for the charging stations at places of purchase (EVSE-POP), which also represent fast-charging stations in the 'P0' scenario, is firstly set to $50 \approx 80 - 2 \cdot \sigma(SOC_{init})$ %-SOC and for the charging stations at parking places somewhere else (EVSE-SWE) to $35 \approx 80 - 3 \cdot \sigma(SOC_{init})$ %-SOC.

4.3.1 Validation runs and discussion

Results for a first validation run parametrized with the *connection indifference levels* described above, 80 (H), 80 (W), 50 (POP), 35 (SWE) in %-SOC, are presented in Figure 42. The figure shows single active power charging curves (blue dots) together with the average load of 100 BEV aggregated over all charging locations for 52 weeks (solid line) in comparison to the average load of 100 EV from Schäuble et al. (2017*a*), first, using the mean $\xi_d = 1.5378$ for the number of charging events per vehicle and per charge day (dotted line) and, second, drawing from the empirical distribution $\xi_d(n)$ for $n = 100$ EV (dashed line). Note that the average load using $\xi_d = 1.5378$ for the number of charging events per vehicle and per charge day is provided for comparison reasons only. The mean of the empirical distribution $\xi_d(n)$ does not converge to this quantity for increasing n because it allows for the possibility that a vehicle is not used on a particular day. In addition, indicators regarding the charged, self-discharged and consumed energy as well as the number of charging events (calculated without intermediate charging events) are provided in total values for the whole simulation horizon of one year and as daily average per BEV.

Figure 42 shows that the overall power level of the average load profile simulated with synPRO-emobility using the parametrization specified above is approximately 5–20 kW above the dashed line with a high workday peak of 35–40 kW in the morning at around 8 a.m and in the evening of 32–35 kW at around 7–8 p.m., a minimum of approximately 8 kW at around 5–6 a.m. in the early workday mornings and a workday afternoon valley of 25–28 kW at around 2–5 p.m. On Saturdays, a broad afternoon to evening peak of 20–25 kW is visible at around 1–7 p.m. On Sundays, a lower afternoon to evening peak of 12–15 kW is visible at around 1–7 p.m. Taking a closer look at the spatial and behavioral influence regarding the driving and the recharging in Figure 43, one can see that the morning peaks originate from distinct charging peaks at work (cf. row 3). The evening peaks result from distinct charging peaks maxing out in the evening at around 6–7 p.m. for the charging at home (cf. row 2). The overall shape of the average synthetic load profile simulated with synPRO-emobility is similar to calculations of other authors also using the MiD data basis (cf. Figure 41).

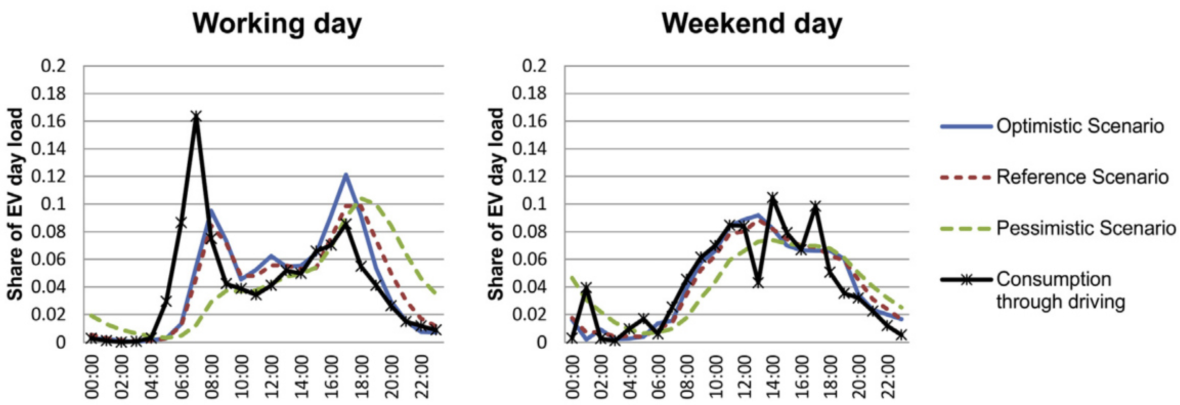


Figure 41: Scenario-specific Charging Curves for Germany on a Working Day (left) and a Weekend Day (right) (Babrowski et al., 2014, p. 286)

In comparison, the average synthetic load profile of Schäuble et al. (2017*b*) has a workday afternoon peak of approximately 23–26 kW at roughly 3–5 p.m. The peaks on the weekend max out at 6–9 kW at around 2–3 p.m. Note that all differences are most likely due to a heterogeneous data basis: the data used by Schäuble et al. (2017*b*) to simulate synthetic load profiles of EV charging is primarily related to company fleets as approximately 80 % of the valid charging operations considered for the model are from company fleet field trials. It is likely that EVs of company fleets are used and rather recharged during working hours which might explain the missing morning and evening peaks. Moreover, it is likely that the vehicles are used less frequently on weekends which may explain the significantly lower load peaks of the average profile on Saturdays or Sundays (also cf. Figure 39). Other company field trials indicate that the driving behavior might be strongly influenced by organizational restrictions and incentives set by the participating companies (Azadfar et al., 2015; Speidel et al., 2012). For that reason the shape of the average synthetic load profiles of Schäuble et al. (2017*b*) cannot be seen as an exact reference for the validation of synPRO-emobility but rather serves as a general guideline of the overall power level.

Note that, regarding the relatively high power levels during the night, it cannot be excluded that this is an algorithmic artifact due to the currently assumed latest arrival until 4 a.m. of the following day (cf. Step 11 in 4.2.1): since the driving and parking time for a trip per day is sampled stochastically independent of the driving and parking time of all other trips on that particular day, the only way to avoid an overshooting of the last arrival time far into the next day, is to assume a latest arrival per day and use rejection sampling in case the condition is violated (i.e. the driving and parking times of all trips of the day are re-sampled). This procedure is primarily relevant for days on which a lot of trips are driven in general or if a lot of trips occur after work since in the latter case the typically long parking times at work usually grant only a relatively small time frame left to allocate the remaining trips. In order to fully assess if this might be the reason for the relatively high power levels during the night, the distribution of the last arrival time has to be further examined. If yes, a possible simple adjustment is to lower the allowed limit of the latest arrival per day based on an analysis of the corresponding MiD data and check if the rejection sampling procedure still provides a reasonable runtime.

Comparing the daily average of the *consumed energy* per BEV $E_{con} = 4.89$ kWh to the overall expected value of the daily consumed energy per car of the MiD data using the daily vehicle use probability of approximately 0.6 and the average of the daily covered distance per car of 82.36 km together with the average nominal consumption weighted with the BEV model frequency of the simulation run $\bar{c}_{nominal} = 13.81$ kWh/100km a positive skewness of approximately 28 % is observable ($E_{con} = 0.6 \cdot 82.36 \cdot 13.81/100 = 6.82$ kWh). The deviation indicates that some or several primary drivers in the simulation used the BEV on a smaller number of days, drove fewer trips per (use) day or covered shorter distances per trip. A combination of the second and the third aspect is most likely due to the very skew and long tailed empirical distribution of the daily covered distance per vehicle (cf. Table 11) which results in a slow convergence of the two corresponding sampling distributions throughout the simulation.

TABLE 11: DISTRIBUTION OF THE COVERED DISTANCE IN KM PER VEHICLE AND PER DAY BASED ON THE MID DATA

Quantity	**Min.**	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
Driven distance in km	0.48	19.31	42.23	82.36	88.91	963.30

The daily average of the *charged energy* per BEV $E_{ch} + E_{imc} = 4.95 + 0.45 = 5.4$ kWh cannot be compared to the ones of the *CROME* (4.34 kWh) and *Get eReady* (10.04 kWh) field trials since both quantities are only reported per day on which a vehicle was charged whereas the calculation in synPRO-emobility relies on all 364 simulation days regardless of charging or not charging the vehicle on a particular day (cf. Table 10). Note that the reported values regarding the charged energy per vehicle and per charge day differ considerably, indicating that the driving behavior of the participants of the *CROME* field trial diverges from that of the *Get eReady* trial in that the participants of the latter charged much more energy per charge day. Simultaneously, they charged less frequently per charge day (1.29) compared to the *CROME* field trial (1.71) indicating a generally different recharge behavior.

In contrast, the average number of charging events per vehicle and per day on which a vehicle was present in a field trial (averaging over the complete data basis of all three field trials) was reported at 0.2857 (Schäuble et al., 2017*b*, p. 257). Compared to snyPRO-emobility (0.77) this quantity is approximately 63 % lower. Similarly, the value of the *MINI E field trial* (0.4) is approximately 48 % lower so that a vehicle in this trial was on average charged every second to third day. The same quantity is also stated by Azadfar et al. (2015, p. 1072). It is important to note here that the *MINI E field trial* better represents the data basis of synPRO-emobility as it was targeted at private households (cf. Table 10). Accordingly, note that the average number of charging events per charge day and per vehicle of the *iZeus* field trial (1.71), which also represents private households, is higher compared to that of the *Get eReady* field trial (1.29) indicating that the all-field-trial average is especially lowered by the latter.

The comparison with respect to field trial targeted at private households (i.e. *MINI E field trial*, *iZeus*) provides evidence that the chosen parametrization regarding the *connection indifference levels* for this first validation run has to be further reduced: results for a second validation simulation run parametrized with the *connection indifference levels*, 50 (H), 50 (W), 20 (POP), 5 (SWE) in %-SOC, are presented in Figure 44 and 45. Note that the indifference levels for all charging locations are lowered by approximately two further standard deviations $\sigma(SOC_{init}) = 2 \cdot 14.2 \approx 30$ %-SOC and therefore deliberately deviate from the average of the hourly medians of the initial battery's SOC upon recharging (cf. Figure 40).

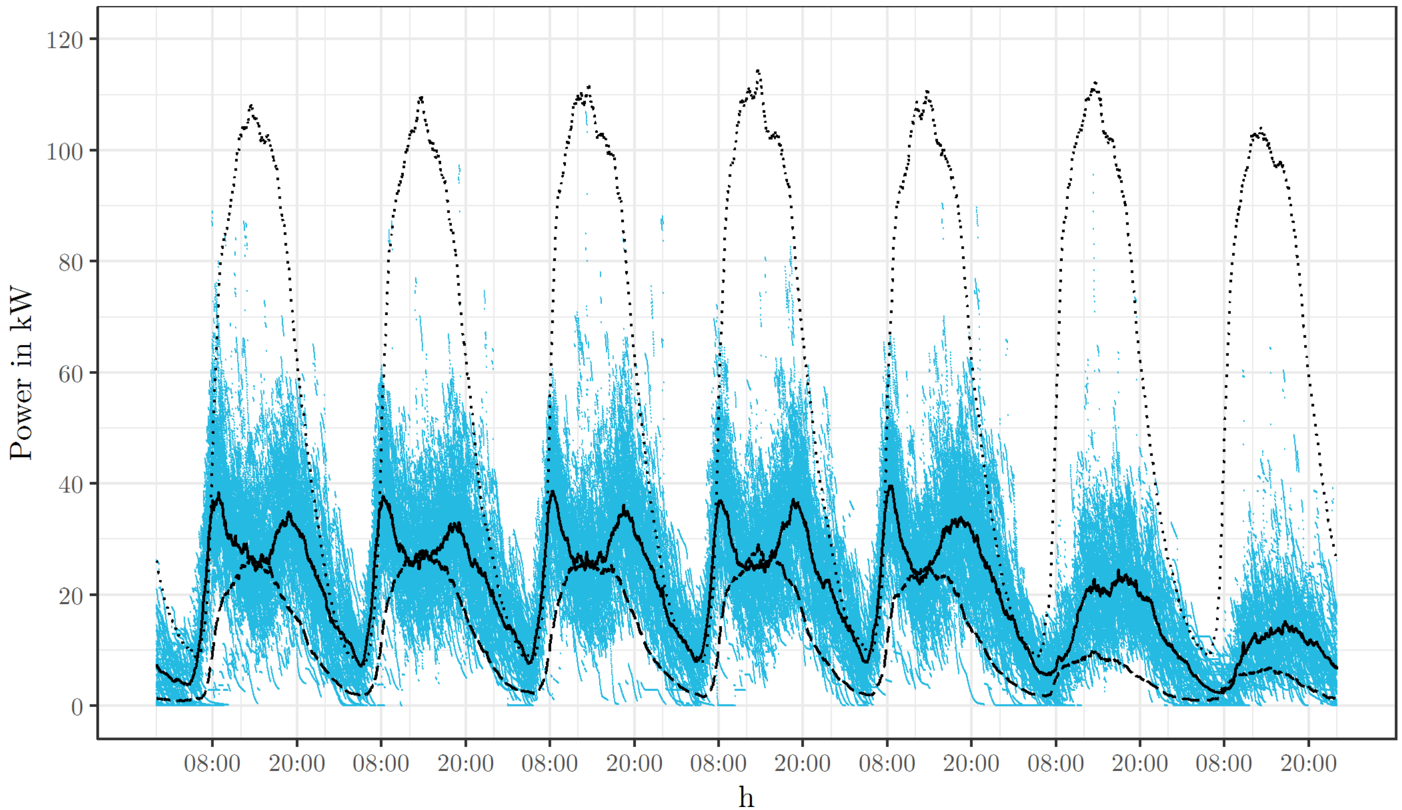
Figure 44 shows that the average power level of synPRO-emobility is better aligned to the dashed line of Schäuble et al. (2017*b*) with respect to workdays. In comparison to the previous simulation run, the heavy morning peaks are lowered more compared to the evening peaks indicating that the reduction of the connection indifference level for the charging at work affected a higher number of parking events.
The daily average *consumed energy* $E_{con} = 4.52$ is lower than in the previous simulation run, which indicates that some BEVs' primary drivers in this run used the vehicle less frequently, drove fewer trips per (use) day or covered shorter distances per trip. Again, this instance traces back to the general methodological limitation of simulations, that a relatively small number of samplings does not guarantee a convergence of the sampling distributions to the underlying empirical distribution. Due to the smaller sampled consumption and a lowered *self-discharged energy* $E_{sdc} = 0.25$, the daily average *charged energy* $E_{ch} + E_{imc} = 4.26 + 0.49 = 4.75$ kWh is also lowered by approximately 12 %.

Regarding the average number of charging events per vehicle and per day and the SOC levels upon recharging, the second validation run provides an ambiguous result: on the one hand, the daily average of the number of charging events per BEV and per day (0.42) is very close to the measured value of the *MINI E field trial* (0.4). On the other hand the chosen level of the *connection indifference levels* does not reflect the findings on the distribution of the initial battery's SOC upon recharging (cf. Figure 40) and the daily average of the number of charging events is approximately 47 % higher compared to the all-field-trial average (0.2857) reported by Schäuble et al. (2017*b*). However, note that the latter value is supposed to be higher because few vehicles were parked for longer periods, i.e. 1–2 weeks which lowered the average (Schäuble et al., 2017*b*, p. 257).
In case the average energy consumption per day and vehicle can be assumed to be approximately equal, the deviation could be explained by smaller battery capacities for the BEV models deployed in synPRO-emobility. However, the average of the nominal battery capacities weighted with the BEV model frequency of the simulation run and adjusted by $\xi_{eff} = 0.85$ results in a capacity of approximately 22 kWh (180 km range at 12.49 kWh/100km) for the average BEV which seems comparable to most reported EV models of the *CROME* and *iZeus* field trials. Note that specific information on the deployed EVs within the *Get eReady* field trial were not available.

If one assumes that the average energy consumption per day and vehicle differs, the deviations of the initial battery's SOC upon recharging could be either explained by different driving behavior or a different average nominal energy consumption. The latter is $\bar{c}_{nominal} = 13.26$ kWh/100km weighted with the specific BEV model frequency of this validation run. Because the latter also seems to be comparable to the reported EV models of the *CROME* and *iZeus* field trials, the most likely reason for the deviations is a different driving behavior resulting from the combined data basis of Schäuble et al. (2017*b*) compared to that used in synPRO-emobility.

Comparing the results of the second validation run to the results obtained using an 'always charging upon arrival' case (most often assumed by other EV charging models, cf. Section 1) which is represented by the *connection indifference levels* 100 (H), 100 (W), 100 (POP), 100 (SWE) %-SOC, one can see that they differ strongly (cf. Figure 63 in B.2). While the daily average of the *consumed energy* per BEV $E_{con} = 4.78$ is slightly lower, the average of the *charged energy* per BEV and per day $E_{ch} + E_{imc} = 6.17$ kWh is approximately 30 % higher. This is due to the fact that the battery is frequently operated between 100 and 95 %-SOC when assuming that a particular BEV always charges the maximum energy upon arrival so that the self-discharged energy maxes out at 1.4 kWh per day and per vehicle, which is an increase of 560% compared to the simulation run from above (cf. Section 4.1.3). The average number of charging events per BEV and day maxes out at 2.23 which is an increase of approximately 530 % and represents the average number of trips conducted per BEV and per day.

Figure 42: SynPRO-emobility Simulation Results: Scenario ‘P0’ + Connection Indifference Levels in %-SOC: 80 (H), 80 (W), 50 (POP), 35 (SWE), Average Load of 100 BEV for 52 Weeks (364 Days) Aggregated Over all Charging Locations

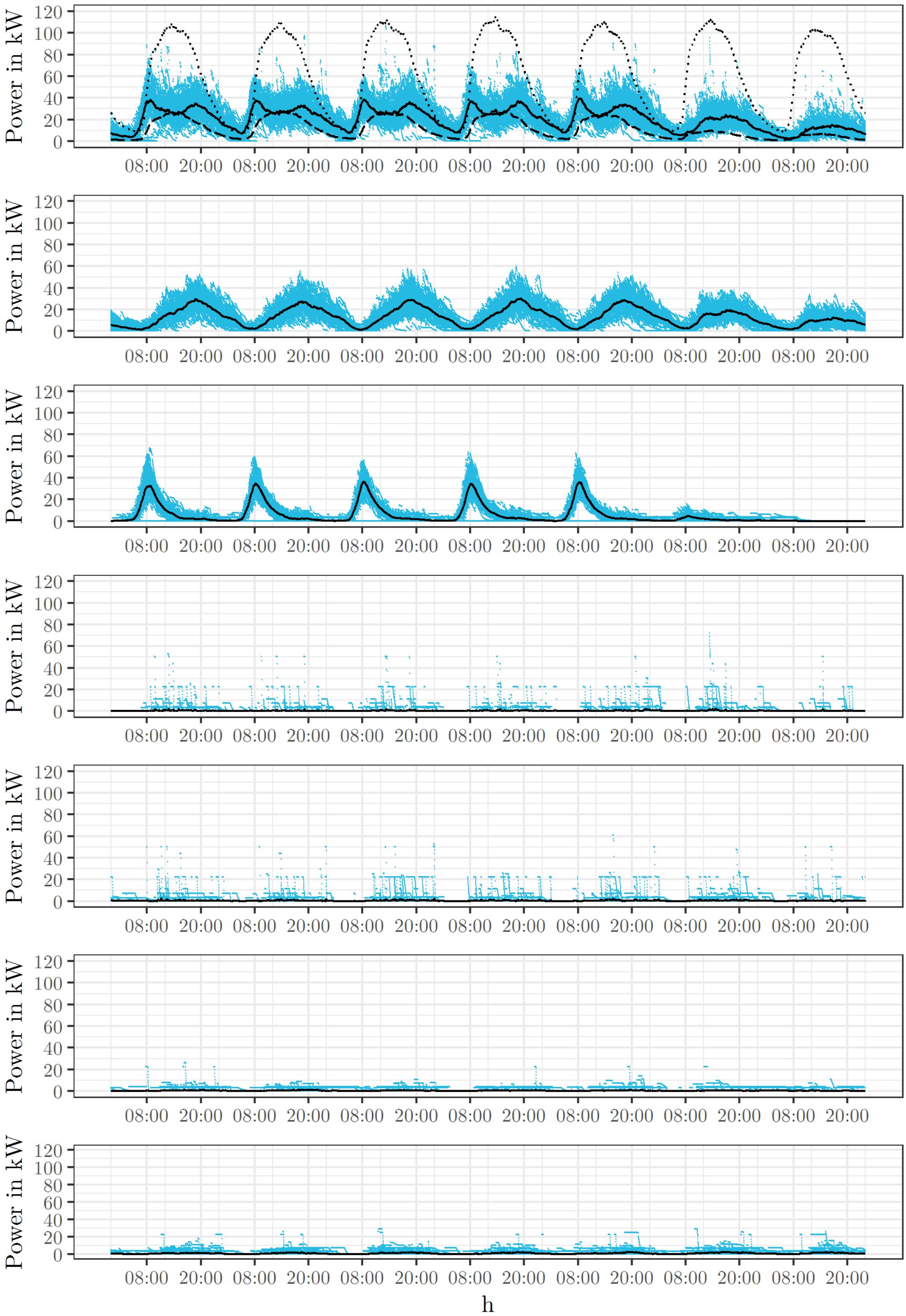


Total annual values
for 100 BEV:
Pmax in kW = 107
Ech in kWh = 180,049
Eimc in kWh = 16,260
Esdc in kWh = 18,929
Econ in kWh = 177,820
No. of charging = 27,980

Daily average per BEV:
Ech in kWh = 4.95
Eimc in kWh = 0.45
Esdc in kWh = 0.52
Econ in kWh = 4.89
No. of charging = 0.77

Blue dots: single active power charging curves of synPRO-emobility
Solid line: average load of synPRO-emobility
Dotted line: average load with no. of charging per vehicle and day $\xi_d = 1.5378$ of Schäuble et al. (2017*b*, p. 262)
Dashed line: average load with no. of charging per vehicle and day drawn from the empirical distribution $\xi_d(100)$ of Schäuble et al. (2017*b*, p. 262)
No. of charging: calculated without intermediate charging

Figure 43: synPRO-emobility Simulation Results: Scenario 'P0' + Connection Indifference Levels in %-SOC: 80 (H), 80 (W), 50 (POP), 35 (SWE), Average Load of 100 BEV for 52 Weeks (364 Days), Aggregated and for Distinct Charging Locations



Plot order (from above): aggregated load, H, W, POP-IC, POP-OC, SWE-IC, SWE-OC

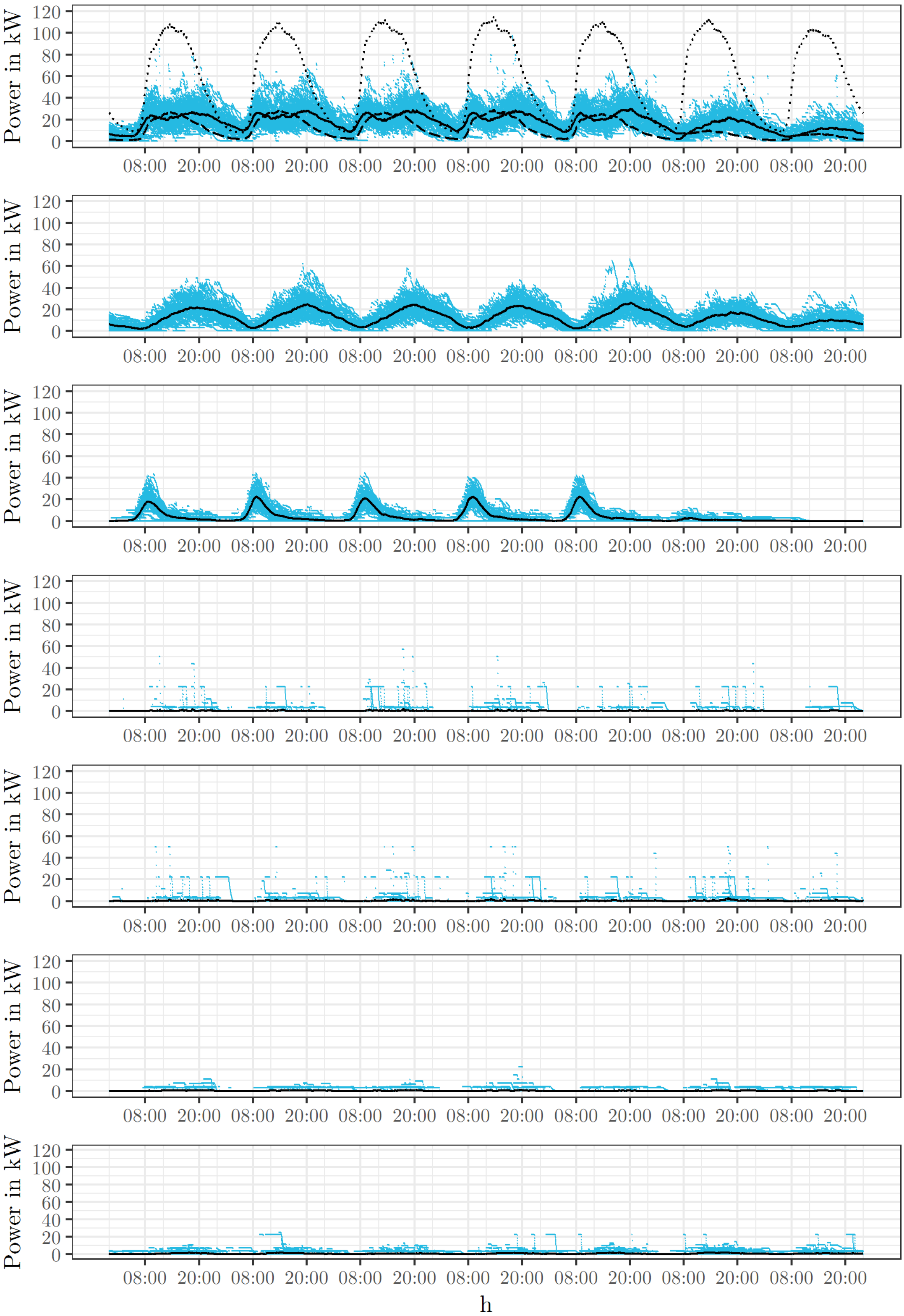
Blue dots: single active power charging curves of synPRO-emobility

Solid line: average load of synPRO-emobility

Dotted line: average load with no. of charging per vehicle and day $\xi_d = 1.5378$ of Schäuble et al. (2017*b*, p. 262)

Dashed line: average load with no. of charging per vehicle and day drawn from the empirical distribution $\xi_d(100)$ of Schäuble et al. (2017*b*, p. 262)

Figure 45: synPRO-emobility Simulation Results: Scenario 'P0' + Connection Indifference Levels in %-SOC: 50 (H), 50 (W), 20 (POP), 5 (SWE), Average Load of of 100 BEV for 52 Weeks (364 Days), Aggregated and for Distinct Charging Locations



Plot order (from above): aggregated load, H, W, POP-IC, POP-OC, SWE-IC, SWE-OC

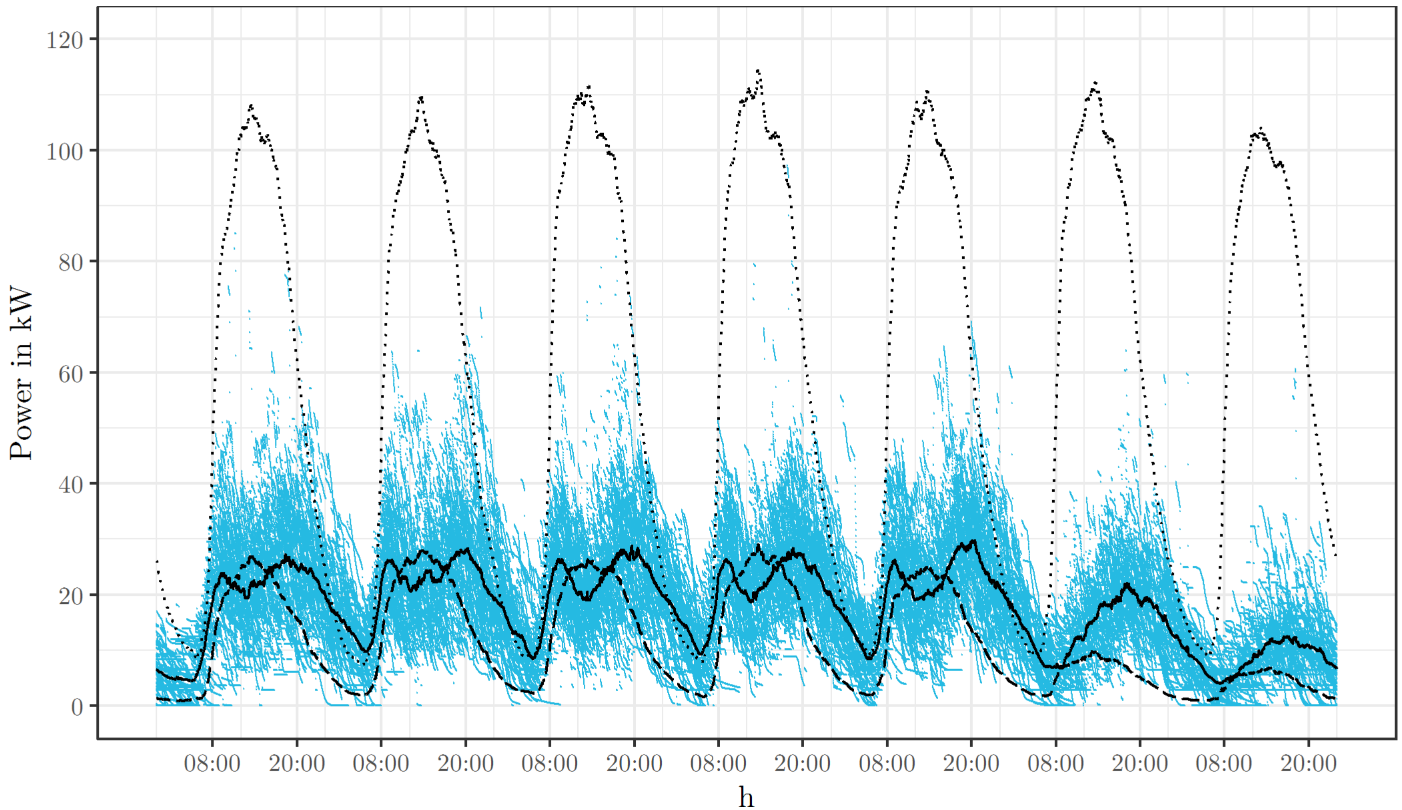
Blue dots: single active power charging curves of synPRO-emobility

Solid line: average load of synPRO-emobility

Dotted line: average load with no. of charging per vehicle and day $\xi_d = 1.5378$ of Schäuble et al. (2017*b*, p. 262)

Dashed line: average load with no. of charging per vehicle and day drawn from the empirical distribution $\xi_d(100)$ of Schäuble et al. (2017*b*, p. 262)

Figure 44: SynPRO-emobility Simulation Results: Scenario ‘P0’ + Connection Indifference Levels in %-SOC: 50 (H), 50 (W), 20 (POP), 5 (SWE), Average Load of 100 BEV for 52 Weeks (364 Days) Aggregated Over all Charging Locations



Total annual values
for 100 BEV:
Pmax in kW = 97
Ech in kWh = 155,142
Eimc in kWh = 17,759
Esdc in kWh = 9,014
Econ in kWh = 164,585
No. of charging = 15,297

Daily average per BEV:
Ech in kWh = 4.26
Eimc in kWh = 0.49
Esdc in kWh = 0.25
Econ in kWh = 4.52
No. of charging = 0.42

Blue dots: single active power charging curves of synPRO-emobility
Solid line: average load of synPRO-emobility
Dotted line: average load with no. of charging per vehicle and day $\xi_d = 1.5378$ of Schäuble et al. (2017*b*, p. 262)
Dashed line: average load with no. of charging per vehicle and day drawn from the empirical distribution $\xi_d(100)$ of Schäuble et al. (2017*b*, p. 262)
No. of charging: calculated without intermediate charging

4.3.2 Critical appraisal

The charging indicators reported for the company fleet field trials *CROME* and *Get eReady* together with findings of other company fleet trials (Azadfar et al., 2015; Speidel et al., 2012) provide strong evidence of a differing driving behavior compared to that of private households represented within synPRO-emobility. This is also reflected in the average synthetic load profiles of Schäuble et al. (2017*b*) since the *Get eReady* field trial dominates the combined data basis used for their generation, resulting in a considerably different shape compared to the average synthetic load profiles simulated with synPRO-emobility. Therefore it can be recommended that further validation attempts should focus solely on field trials targeted at private households.

The shape of the average synthetic load profile simulated with synPRO-emobility is similar to the share of EV day load derived by Babrowski et al. (2014, p. 286) also relying on the MiD data. Additionally, the indicator provided by the *MINI E field trial* targeted at private households, provides evidence of a relatively good fit regarding the second simulation run parametrized with the connection indifference levels 50 (H), 50 (W), 20 (POP), 5 (SWE) %-SOC and a connection sensitivity of 1 %-SOC. However, this parametrization leads to similar values for the average battery's SOC upon recharging throughout the simulation, which is contradictory to the findings regarding the company fleet trials mentioned above (cf. Figure 40). In order to further evaluate the second validation run it is recommended to compare the distribution of the initial battery's SOC upon recharging with empirical charging data of further field trials targeted at private households.

The relatively high power levels during the night indicate that simulation results of synPRO-emobility feature many arrivals in the late evening. This might be an algorithmic artifact resulting from the methodological approach to generate driving profiles using rejection sampling for the determination of driving and parking times (which on their part determine the departure and arrival times of each trip) limited to a latest arrival before 04:00 a.m. of the following day. Therefore, a further assessment should concentrate on a comparison of the distribution of the last arrival time per day of the MiD data to the one resulting from synPRO-emobility.

Additionally, the average load profiles of synPRO-emobility do not incorporate information on the regularities (or irregularities) of driving behavior beyond a daily resolution (e.g. weekly use patterns) due to the fact that the MiD data only provides information on the driving behavior of households for single days. In order to incorporate these patterns one need to analyze panel data, for example from the *German Mobility Panel* (MOP).

Overall, a validation of synPRO-emobility seems to be difficult because of the heterogeneity of empirical findings related to EV charging. One can conclude that that a validation with data from field trials is in general problematic since every trial is specific and specialized even though the overall user group may be similar. Moreover, the empirical charging data available in the context of this work is not sufficient to validate the model with regard to the average load profile of distinct charging stations, different charging preferences or different household types. For that matter the following simulation results are denoted as 'exemplary'.

4.3.3 Impact of different household types and charging preferences

This subsection briefly summarizes three further simulation runs in order to demonstrate the possible impact that sociodemographically differentiated driving behavior and differing charging preferences might have on distribution grids compared to the average synthetic load profile of the validation section. All simulation runs were performed with the same parametrization as in Section 4.3 (if not stated differently) and compared to the second simulation with *connection indifference levels* of 50 (H), 50 (W), 20 (POP), 5 (SWE) %-SOC.

Figure 65 to 68 in B.2 show the average load aggregated over all charging locations and for distinct charging locations for 100 BEV from 2Am1Cu18 households (family households with at least one child under 18 years). One can see that the fleet is charged with approximately 19 % more energy per year compared to the average. The annual peak load $P_{max} = 93$ kW over all charging locations and at home $P_{max}^{EVSE-H} = 66$ kW is approximately equal to the average but the annual peak load at work $P_{max}^{EVSE-W} = 69$ kW is approximately 57 % higher compared to the average.

Figure 69 to 72 show the average load aggregated over all charging locations and for distinct charging locations for 100 BEV from 2Ay60p households (two person households with the youngest person above 60 years). One can see that the fleet is charged with approximately 21 % less energy per year compared to the average. The annual peak load $P_{max} = 79$ kW over all charging locations is approximately 19 % lower. The annual peak load at home $P_{max}^{EVSE-H} = 53$ kW is approximately 20 % lower. At work $P_{max}^{EVSE-W} = 13$ kW is approximately 70 % lower compared to the average.

Figure 73 to 76 show the average load aggregated over all charging locations and for distinct charging locations for 100 BEV using the *connection indifference levels* 50 (H), 50 (W), 80 (POP), 5 (SWE) %-SOC which represent a preference for fast-charging (e.g. at supermarkets, shopping malls). One can see that the annual peak load $P_{max} = 136$ kW over all charging locations is approximately 40 % higher. The annual peak load at fast-charging stations at supermarkets inside the city $P_{max}^{EVSE-POP-IC} = 103$ kW is approximately 80 % higher. At fast charging stations at supermarkets outside the city $P_{max}^{EVSE-POP-OC} = 82$ kW is 64 % higher compared to the reference charging preferences.

5 Conclusion and outlook

This work provided a detailed examination of household's driving behavior in Germany using different robust statistical tests to identify effects in the sample of the MiD 2008 survey. The results lead to a possible differentiation of driving behavior in Germany regarding the different numerically and categorically dependent variables of interest in the context of this work. This differentiation was subsequently used to generate driving profiles in order to simulate EV load profiles within synPRO-emobility. The representation of different charging locations was achieved by a spatial evaluation of the MiD dataset and the modeling of a SOC-dependent recharge behavior using a binary univariate logit model for the connection decision at different parking places.

A number of conclusions and recommendations can be made in relation to the the continuing development and validation of EV charging models. First, it was found that driving behavior in the MiD sample is primarily influenced by the household type (especially by the presence of children, the overall number of household members and their age) as well as the occupation of the ICEV's primary driver (specified as working, e.g. full-time, halftime, student or apprentice, and non-working such as homemakers, pensioners and unemployed) and his vehicle use frequency. The household's place of residence (more precisely the agglomerations: rural, urban, city) only has a minor influence. However with regard to ICEV purchasing it shows a significant influence just as the the household's economic status and the household type. Regarding temporal influences, the weekday of the vehicle use has an noticeable influence on the driving behavior whereas the season in which the vehicle is used is completely negligible. In order to generalize these findings to the population in Germany one could statistically test selected identified effects with respect to the new results expected in late 2017 of the presently ongoing MiD 2016 inquiry.

Second, charging preferences regarding the charging location can be modeled using a *univariate logit model* based on the battery's SOC upon recharging. However, one has to keep in mind that this procedure assumes that EV users have a very high *battery-interaction-style* and neglects the supplemental finding concerning their levels of *comfortable range* (Franke and Krems, 2013). Future modeling approaches could focus on several influencing factors fitting a multivariate logistic regression model based on empirical charging data. Similarly, the procedure to estimate the number of available BEVs per household using a simple BEV market penetration rate could be enhanced by a more detailed approach considering findings on purchase intentions of early EV adopters, such as the binary logistic regression model of Ensslen et al. (2015).

Third, it could be demonstrated that EV load profile models relying on driving data from mobility surveys together with the classic assumption of *charging upon arrival for every parking event*, without considering possible charging preferences regarding the battery's SOC upon arrival (also with respect to different charging locations), do in fact lead to heavily overestimated average synthetic load profiles compared to empirical findings of different field trials. Note that this is not the case for models relying on empirical charging data.

Fourth, the validation results also indicate that charging preferences modeled by an SOC-dependent connection probability for different charging locations and qualitatively calibrated using findings from literature lead to a number of charging events per day and per vehicle comparable to a field trial from Germany targeted on private households. Additionally, the overall shape of the daily average load profile is similar to synthetic load profiles derived by Babrowski et al. (2014) relying on the same driving data (MiD 2008). Exemplary simulations suggested that differing charging preferences regarding the charging location and the impact of sociodemographically differentiated BEV users are likely to have a serious impact on distribution grids compared to the average synthetic load profile of BEV charging. This has to be further assessed by load flow simulations, though, for which the synthetic load profiles of different charging locations can provide a valuable data basis.

Fifth, the results also suggest that average synthetic load profiles based upon charging data from field trials targeted at company fleets are not suitable for a validation since their shape differs substantially from those derived from mobility survey data of private households in Germany. Similarly, charging indicators from company fleet trials also show deviating values, for example with respect to the average of the initial battery's SOC upon arrival. Future validation attempts should therefore focus only on charging data acquired from field trials targeted at private households and assess the corresponding distribution of the initial battery's SOC upon arrival in comparison to the one resulting from the simulation. However, future modeling approaches could combine the MiD data with data from company fleet trials or the KiD database to achieve a better representation of trips related to commercial transportation since the representativeness of the MiD data is limited with respect to regular job-related trips apart from intermittent business trips. Moreover, since the MiD basis only provides information on households' driving behavior of single days it could be enhanced with information on regularities (or irregularities) of driving behavior beyond a daily resolution such as weekly trip patterns using the MOP data.

Sixth, the relatively high power level during nighttime of all simulation results suggest that the used rejection sampling method to determine temporal trip profiles by limiting the latest arrival per day to 04:00 a.m. might lead to an overestimation of arrivals in the evening. This has to be further assessed by comparing the distribution of the last arrival time per day and may be resolved by adjusting the parameter accordingly.

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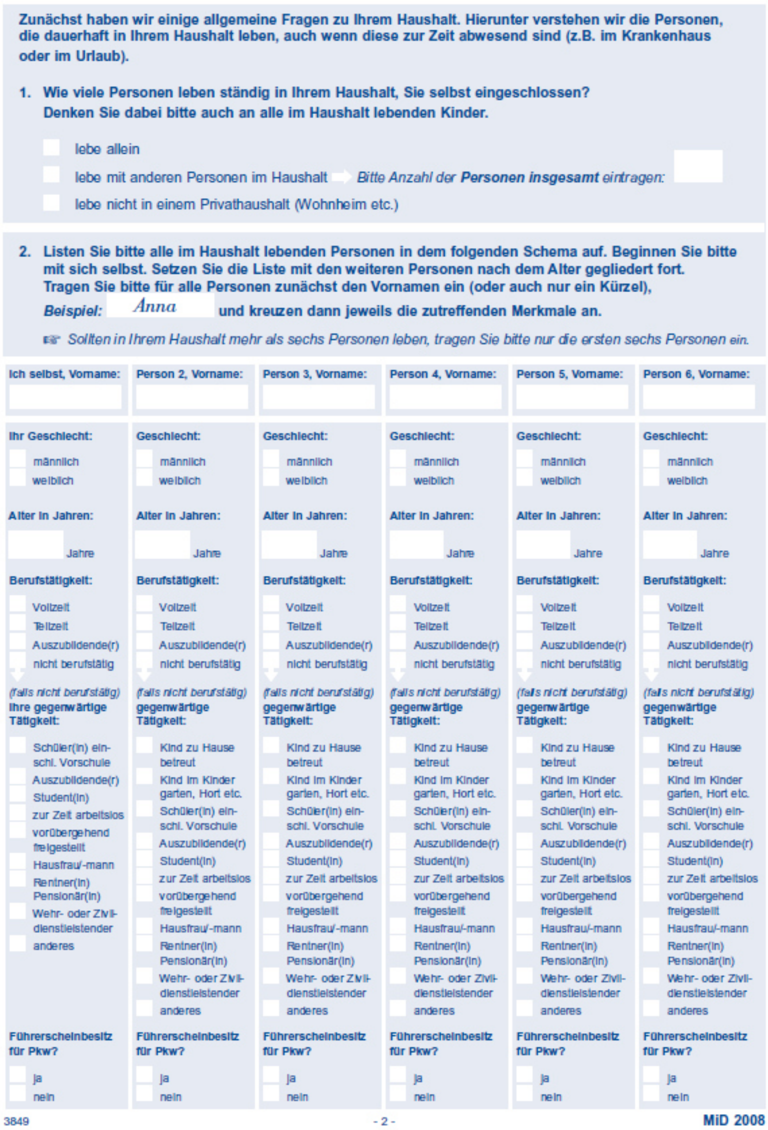
A Appendix for Chapter 3

A.1 Additional information on MiD

This section lists important derived variables of the MiD datasets referred to throughout this work and provides further information on the underlying data generating survey material. For more information, see (Follmer et al., 2008, 2010*c*,*d*,*e*,*f*,*g*,*h*,*i*,*j*):

A.1.1 Survey material

Household level



Zunächst haben wir einige allgemeine Fragen zu Ihrem Haushalt. Hierunter verstehen wir die Personen, die dauerhaft in Ihrem Haushalt leben, auch wenn diese zur Zeit abwesend sind (z.B. im Krankenhaus oder im Urlaub).

1. Wie viele Personen leben ständig in Ihrem Haushalt, Sie selbst eingeschlossen? Denken Sie dabei bitte auch an alle im Haushalt lebenden Kinder.

- lebe allein
- lebe mit anderen Personen im Haushalt → *Bitte Anzahl der* ***Personen insgesamt*** *eintragen:*
- lebe nicht in einem Privathaushalt (Wohnheim etc.)

2. Listen Sie bitte alle im Haushalt lebenden Personen in dem folgenden Schema auf. Beginnen Sie bitte mit sich selbst. Setzen Sie die Liste mit den weiteren Personen nach dem Alter gegliedert fort. Tragen Sie bitte für alle Personen zunächst den Vornamen ein (oder auch nur ein Kürzel), ***Beispiel:*** Anna **und kreuzen dann jeweils die zutreffenden Merkmale an.**

Sollten in Ihrem Haushalt mehr als sechs Personen leben, tragen Sie bitte nur die ersten sechs Personen ein.

Ich selbst, Vorname:	Person 2, Vorname:	Person 3, Vorname:	Person 4, Vorname:	Person 5, Vorname:	Person 6, Vorname:
Ihr Geschlecht: männlich weiblich	**Geschlecht:** männlich weiblich	**Geschlecht:** männlich weiblich	**Geschlecht:** männlich weiblich	**Geschlecht:** männlich weiblich	**Geschlecht:** männlich weiblich
Alter in Jahren: Jahre	**Alter in Jahren:** Jahre	**Alter in Jahren:** Jahre	**Alter in Jahren:** Jahre	**Alter in Jahren:** Jahre	**Alter in Jahren:** Jahre
Berufstätigkeit: Vollzeit Teilzeit Auszubildende(r) nicht berufstätig	**Berufstätigkeit:** Vollzeit Teilzeit Auszubildende(r) nicht berufstätig	**Berufstätigkeit:** Vollzeit Teilzeit Auszubildende(r) nicht berufstätig	**Berufstätigkeit:** Vollzeit Teilzeit Auszubildende(r) nicht berufstätig	**Berufstätigkeit:** Vollzeit Teilzeit Auszubildende(r) nicht berufstätig	**Berufstätigkeit:** Vollzeit Teilzeit Auszubildende(r) nicht berufstätig
(falls nicht berufstätig) **Ihre gegenwärtige Tätigkeit:** Schüler(in) einschl. Vorschule Auszubildende(r) Student(in) zur Zeit arbeitslos vorübergehend freigestellt Hausfrau/-mann Rentner(in) Pensionär(in) Wehr- oder Zivildienstleistender anderes	*(falls nicht berufstätig)* **gegenwärtige Tätigkeit:** Kind zu Hause betreut Kind im Kindergarten, Hort etc. Schüler(in) einschl. Vorschule Auszubildende(r) Student(in) zur Zeit arbeitslos vorübergehend freigestellt Hausfrau/-mann Rentner(in) Pensionär(in) Wehr- oder Zivildienstleistender anderes	*(falls nicht berufstätig)* **gegenwärtige Tätigkeit:** Kind zu Hause betreut Kind im Kindergarten, Hort etc. Schüler(in) einschl. Vorschule Auszubildende(r) Student(in) zur Zeit arbeitslos vorübergehend freigestellt Hausfrau/-mann Rentner(in) Pensionär(in) Wehr- oder Zivildienstleistender anderes	*(falls nicht berufstätig)* **gegenwärtige Tätigkeit:** Kind zu Hause betreut Kind im Kindergarten, Hort etc. Schüler(in) einschl. Vorschule Auszubildende(r) Student(in) zur Zeit arbeitslos vorübergehend freigestellt Hausfrau/-mann Rentner(in) Pensionär(in) Wehr- oder Zivildienstleistender anderes	*(falls nicht berufstätig)* **gegenwärtige Tätigkeit:** Kind zu Hause betreut Kind im Kindergarten, Hort etc. Schüler(in) einschl. Vorschule Auszubildende(r) Student(in) zur Zeit arbeitslos vorübergehend freigestellt Hausfrau/-mann Rentner(in) Pensionär(in) Wehr- oder Zivildienstleistender anderes	*(falls nicht berufstätig)* **gegenwärtige Tätigkeit:** Kind zu Hause betreut Kind im Kindergarten, Hort etc. Schüler(in) einschl. Vorschule Auszubildende(r) Student(in) zur Zeit arbeitslos vorübergehend freigestellt Hausfrau/-mann Rentner(in) Pensionär(in) Wehr- oder Zivildienstleistender anderes
Führerscheinbesitz für Pkw? ja nein	**Führerscheinbesitz für Pkw?** ja nein	**Führerscheinbesitz für Pkw?** ja nein	**Führerscheinbesitz für Pkw?** ja nein	**Führerscheinbesitz für Pkw?** ja nein	**Führerscheinbesitz für Pkw?** ja nein

3849 - 2 - **MiD 2008**

Figure 46: Extract of MiD survey material intended to gather information on participating households and their members (Follmer et al., 2008)

4. Wie viele der folgenden Fahrzeuge gibt es in Ihrem Haushalt?

☞ *Tragen Sie bitte jeweils die Anzahl ein!*

- funktionstüchtige Fahrräder
- Motorräder, Mopeds, Mofas
- Autos (einschließlich Kombi / Van / Kleinbus / Wohnmobil)

Falls laut Frage 4 ***keine*** *Autos im Haushalt vorhanden sind:*

5. Aus welchen der folgenden Gründen hat Ihr Haushalt kein Auto?

☞ *Bitte kreuzen Sie alles Zutreffende an.*

- kein Auto benötigt
- bewusster Verzicht
- Anschaffung oder Unterhalt zu teuer
- gesundheitliche Gründe
- Altersgründe
- andere Gründe

6. Für die Fortführung der Befragung benötigen wir die Telefonnummer(n), über die Ihr Haushalt am besten zu erreichen ist.

☞ *Bitte tragen Sie dazu die vollständige Nummer(n) ein:*

1) *Vorwahl* *Anschluss*   2) *Vorwahl* *Anschluss*

7. Wie hoch ist das monatliche Nettoeinkommen Ihres Haushalts in Euro ungefähr?
Bitte beziehen Sie alle im Haushalt verfügbaren Einkommensarten ein – also die monatliche Summe aus Lohn, Gehalt, Einkommen aus selbständiger Tätigkeit, Rente oder Pension, jeweils nach Abzug von Steuern und Sozialversicherungsbeiträgen für alle Haushaltsmitglieder. Dazu gehören auch Leistungen wie Kindergeld, Wohngeld oder Sozialhilfe oder sonstige Einkünfte.
Ihre Angabe wird – wie auch alle anderen Angaben in diesem Interview – selbstverständlich vollständig anonym gehalten, so dass keine Rückschlüsse auf Ihre Person selbst möglich sind. Die Ergebnisse der Befragung sollen u.a. nach dem Einkommen ausgewertet werden.

- bis unter 500 Euro pro Monat
- 500 bis unter 900 Euro pro Monat
- 900 bis unter 1.500 Euro pro Monat
- 1.500 bis unter 2.000 Euro pro Monat
- 2.000 bis unter 2.600 Euro pro Monat
- 2.600 bis unter 3.000 Euro pro Monat
- 3.000 bis unter 3.600 Euro pro Monat
- 3.600 bis unter 4.000 Euro pro Monat
- 4.000 bis unter 4.600 Euro pro Monat
- 4.600 bis unter 5.000 Euro pro Monat
- 5.000 bis unter 5.600 Euro pro Monat
- 5.600 bis unter 6.000 Euro pro Monat
- 6.000 bis unter 6.600 Euro pro Monat
- 6.600 bis unter 7.000 Euro pro Monat
- mehr als 7.000 Euro pro Monat

Vielen Dank für das Ausfüllen des Fragebogens!

Bitte vergessen Sie nicht, den ausgefüllten Bogen in dem Freiumschlag portofrei an infas zurückzuschicken.

3849   - 4 -   **MiD 2008**

Figure 47: Extract of MiD survey material intended to gather information on the availability of cars and the net income per month of participating households (Follmer et al., 2008)

Vehicle level

3. **Bitte geben Sie zu jedem Auto (einschließlich Kombi / Van / Kleinbus /Wohnmobil) in Ihrem Haushalt die folgenden Merkmale an.**
☞ *Falls es mehr als drei Autos in Ihrem Haushalt gibt, wählen Sie bitte die aus, die am häufigsten gefahren werden! Falls es kein Auto in Ihrem Haushalt gibt, machen Sie bitte weiter mit Frage 4!*

Auto 1	Auto 2	Auto 3
Hersteller:	**Hersteller:**	**Hersteller:**
Typ / Modell:	**Typ / Modell:**	**Typ / Modell:**
Motorleistung: PS oder kW	**Motorleistung:** PS oder kW	**Motorleistung:** PS oder kW
Baujahr / Erstzulassung: *bitte Jahr eintragen!*	**Baujahr / Erstzulassung:** *bitte Jahr eintragen!*	**Baujahr / Erstzulassung:** *bitte Jahr eintragen!*
Fahrzeug im Haushalt seit: *bitte Jahr eintragen!*	**Fahrzeug im Haushalt seit:** *bitte Jahr eintragen!*	**Fahrzeug im Haushalt seit:** *bitte Jahr eintragen!*
gegenwärtiger km-Stand: km	**gegenwärtiger km-Stand:** km	**gegenwärtiger km-Stand:** km
geschätzte Fahrleistung pro Jahr: km	**geschätzte Fahrleistung pro Jahr:** km	**geschätzte Fahrleistung pro Jahr:** km
Antriebsart: Benzin; Diesel; Gas; Hybrid (Kombination Diesel/Benzin mit Elektroantrieb); Elektroantrieb; anderes	**Antriebsart:** Benzin; Diesel; Gas; Hybrid (Kombination Diesel/Benzin mit Elektroantrieb); Elektroantrieb; anderes	**Antriebsart:** Benzin; Diesel; Gas; Hybrid (Kombination Diesel/Benzin mit Elektroantrieb); Elektroantrieb; anderes
Hauptnutzer(in) im Haushalt: ich selbst; andere Person: *Bitte Personennummer aus Seite 2 eintragen:*	**Hauptnutzer(in) im Haushalt:** ich selbst; andere Person: *Bitte Personennummer aus Seite 2 eintragen:*	**Hauptnutzer(in) im Haushalt:** ich selbst; andere Person: *Bitte Personennummer aus Seite 2 eintragen:*
üblicher Stellplatz: auf dem eigenen Grundstück? ***weiter mit Auto 2***; in unmittelbarer Nähe von Grundstück/Wohnung; in weiterer Entfernung von Grundstück/Wohnung; unterschiedlich	**üblicher Stellplatz:** auf dem eigenen Grundstück? ***weiter mit Auto 3***; in unmittelbarer Nähe von Grundstück/Wohnung; in weiterer Entfernung von Grundstück/Wohnung; unterschiedlich	**üblicher Stellplatz:** auf dem eigenen Grundstück? ***weiter mit Frage 4, nächste Seite***; in unmittelbarer Nähe von Grundstück/Wohnung; in weiterer Entfernung von Grundstück/Wohnung; unterschiedlich
Müssen Sie nach einer Abstellmöglichkeit für diesen Pkw bei Ihnen zu Hause... nie suchen; manchmal suchen; immer suchen; unterschiedlich?	**Müssen Sie nach einer Abstellmöglichkeit für diesen Pkw bei Ihnen zu Hause...** nie suchen; manchmal suchen; immer suchen; unterschiedlich?	**Müssen Sie nach einer Abstellmöglichkeit für diesen Pkw bei Ihnen zu Hause...** nie suchen; manchmal suchen; immer suchen; unterschiedlich?

3849 - 3 - **MiD 2008**

Figure 48: Extract of MiD survey material intended to gather information on available cars of participating households (Follmer et al., 2008)

Trip level

Figure 49 shows an extract of the survey material filled out by participants in order to gather information on important *way* variables:

Wegeblatt für: Deine Wege außer Haus am:

	Um wie viel Uhr hast Du Deinen Weg begonnen?	Warum und wozu hast du den Weg gemacht? (z.B. zur Schule, Freunde besucht, zum Sport)	Wohin bist Du gegangen oder gefahren? (bitte gib die Adresse so genau wie möglich an)	Wie bist Du dorthin gekommen? (z.B. zu Fuß, mit dem Bus, mit dem Fahrrad)	Bist Du mit jemandem zusammen unterwegs gewesen? (Wenn ja, mit wie vielen anderen Personen?)	Wie weit war es ungefähr?	Um welche Uhrzeit bist Du dort angekommen?
1	: Uhr					km	: Uhr
2	: Uhr					km	: Uhr
3	: Uhr					km	: Uhr
4	: Uhr					km	: Uhr

FIGURE 49: EXTRACT OF MID SURVEY MATERIAL INTENDED TO GATHER INFORMATION ON EXECUTED WAYS ON THE SURVEY DUE DAY (FOLLMER ET AL., 2008)

A.1.2 Important derived survey variables

Household level

- *oek_stat - ökonomischer Status des Haushalts* (household's economic status)
  - 1: sehr niedrig (very low)
  - 2: niedrig (low)
  - 3: mittel (medium)
  - 4: hoch (high)
  - 5: sehr hoch (very high)
  - Note, that this variable was formed using the principle of equivalent income allowing for a better comparability. For that matter, the household's net income per month is divided by a weighted sum of the number of household members. The weighting is determined by age and the household size. (cf. figure 50)
- *ktyp_zsg - BBSR Zusammengefasster Kreistyp nach ROB2005* (place of residence)
  - 1: Kernstädte (cities)
  - 2: Verdichtete Kreise (urban areas)

  - 3: Ländliche Kreise (rural areas)
  - Note: classification follows (Adam et al., 2005)

- *hhtyp - Haushaltstyp: differenziert nach Haushaltsgröße und Alter* (household type)
  - 1: Einpersonenhh_Person 18 bis < 30 Jahre (household with one adult, between 18 and 30 years old - 1A1830)
  - 2: Einpersonenhh_Person 30 bis < 60 Jahre (household with one adult, between 30 and 60 years old - 1A3060)
  - 3: Einpersonenhh_Person 60 Jahre und älter (household with one adult, 60 years or older - 1A60p)
  - 4: HH mit zwei Erwachsenen_jüngste Person 18 bis < 30 Jahre (household with two adults, youngest person is between 18 and 30 years old - 2Ay1830)
  - 5: HH mit zwei Erwachsenen_jüngste Person 30 bis < 60 Jahre (household with two adults, youngest person is between 30 and 60 years old - 2Ay3060)
  - 6: HH mit zwei Erwachsenen_jüngste Person 60 Jahre und älter (household with two adults, youngest person is 60 years or older - 2Ay60p)
  - 7: HH mit drei und mehr erwachsenen Personen (household with three or more adult persons - 3mA)
  - 8: HH mit mindestens einem Kind unter 6 Jahre (household with minimum one child under 6 years - 2Am1Cu6)
  - 9: HH mit mindestens einem Kind unter 14 Jahre (household with minimum one child under 14 years - 2Am1Cu14)
  - 10: HH mit mindestens einem Kind unter 18 Jahre (household with minimum one child under 18 years - 2Am1Cu18)
  - 11: Alleinerziehende (single parents - SP)

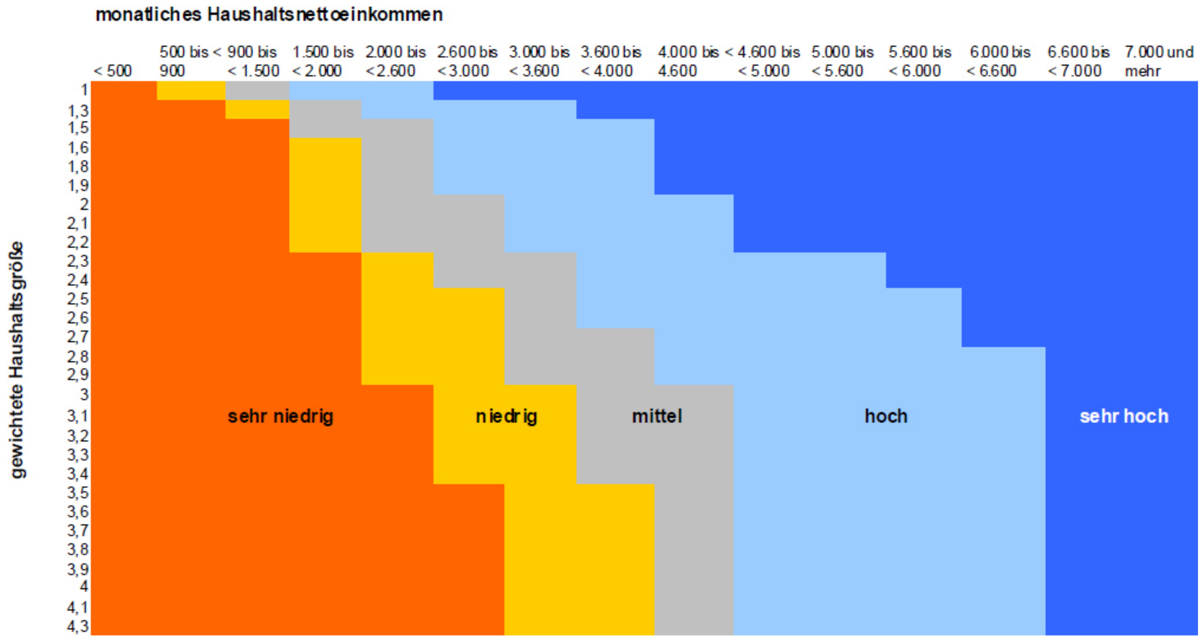


FIGURE 50: CLASSIFICATION MATRIX FOR HOUSEHOLD'S ECONOMIC STATUS USING THE NET INCOME PER MONTH AND A WEIGHTED HOUSEHOLD SIZE (FOLLMER ET AL., 2010*h*, P. 5)

Person level

- *p031 - Und wie häufig benutzen Sie ein Auto?* (vehicle use frequency)
  - 1: täglich bzw. fast täglich (daily or almost daily)
  - 2: an 1-3 Tagen pro Woche (weekly)
  - 3: an 1-3 Tagen pro Monat (monthly)
  - 4: seltener als monatlich (rarely)
  - 5: nie bzw. fast nie (never or almost never; not used)

Vehicle level

- *stichtag - Stichtag (Wochentag)* (weekday)
  - 1: Montag (workday)
  - 2: Dienstag (workday)
  - 3: Mittwoch (workday)
  - 4: Donnerstag (workday)
  - 5: Freitag (workday)
  - 6: Samstag (Saturday)
  - 7: Sonntag (Sunday)

- *h044 - Wer in Ihrem Haushalt nutzt dieses Fahrzeug am häufigsten?* (main user/primary driver)
  - Personennummer Wertebereich: 1 bis 8 (person number of the household member)
  - 96: keine eindeutige Zuordnung möglich (not clearly specifiable)
  - 97: verweigert (rejected)
  - 98: weiß nicht (don't know)
  - 99: keine Angabe (not specified)
- *besch_hn - Beschäftigung Hauptnutzer (Basis hp_besch aus Personendatensatz)* (main user/primary driver's occupation)
  - 1: Berufstätige(r) - Vollzeit (fulltime)
  - 2: Beruftätige(r) - Teilzeit, 11 bis unter 35 Stunden/Woche (halftime)
  - 3: Berufstätige(r) ohne Angabe zum Unfang (employed but no further information; not used)
  - 4: Auszubildende(r) (apprentice)
  - 5: Schüler(in) (einschließlich Vorschule) (pupil/student, primary school included; not used)
  - 6: Student(in) (student)
  - 7: Kind zu Hause betreut (childcare at home; not used)
  - 8: Kind betreut im Kindergarten, Krippe, Tagesmutter etc. (childcare in nursery or kindergarten; not used)
  - 9: zurzeit arbeitslos (unemployed)
  - 10: vorübergeh. freigest. z.B. Mutterschaftsurl., Elternzeit (unemployed)
  - 11: Hausfrau — Hausmann (homemaker)
  - 12: Rentner(in) — Pensionär(in) (pensioner)
  - 13: Wehr- oder Zivildienstleistende(r), Freiwilligendienst (military/civil service; not used)
  - 14: andere Tätigkeit (other occupation; not used)
  - 99: keine Angabe (not specified; not used)

Trip level

- *w01 - War der Ausgangspunkt Ihres ersten Weges zu Hause oder woanders?* (place of departure of the first trip)
  - 1: zu Hause (at home)
  - 2: Arbeitsplatz (work place)
  - 3: woanders in Ihrer Stadt oder Ihrem Ort (somewhere else inside city)
  - 4: woanders außerhalb Ihrer Stadt oder Ihrem Ort (somewhere else outside city)
  - 301: bei rbW nicht erhoben (not inquired for rbW trips)
  - 302: ab zweitem Weg nicht erhoben (not inquired from the second trip on)
  - 303: erfasster erster Weg ist Rückweg (inquired first trip is way back)
- *w13 - Waren Sie zu einem Ziel innerhalb oder außerhalb Ihrer Stadt oder Ihrem Ort unterwegs?* (destination of the trip)
  - 1: zu Hause (at home)
  - 2: Arbeitsplatz (work place)
  - 3: anderes Ziel innerhalb der Stadt oder des Ortes (somewhere else inside city)
  - 4: anderes Ziel außerhalb der Stadt oder des Ortes (somewhere else outside city)
  - 5: Rundweg (round trip)
  - 7: verweigert (rejected)
  - 8: weiß nicht (don't know)
  - 9: keine Angabe (not specified)
  - 301: bei rbW nicht erhoben (not inquired for rbW trips)
  - 304: bei Rückweg nicht erhoben (not inquired for way back)
  - 305: bei Zweck Kita/Kindergarten nicht erhoben (not inquired for way with trip purpose day-care center/kindergarten)
- *w04 - Wegezweck* (trip purpose)
  - 1: Erreichen des Arbeitsplatzes (reaching work place)
  - 2: dienstlich oder geschäftlich (absent on business)
  - 3: Erreichen der Ausbildungsstätte oder Schule (reaching apprenticing company or school)
  - 4: Einkauf (purchasing)

- 5: private Erledigungen (private errand)
- 6: Bringen oder Holen von Personen (bringing or fetching people)
- 7: Freizeitaktivität (leisure activity)
- 8: nach Hause (to home)
- 9: Rückweg vom vorherigen Weg (way back from previous trip)
- 10: andere Aktivität (other activity)
- 11: Begleitung Erwachsener (accompanying of adults)
- 31: zur Schule oder Vorschule (to secondary school or primary school)
- 32: Kindertagesstätte oder Kindergarten (day-care center or kindergarten)
- 97: verweigert (rejected)
- 98: weiß nicht (don't know)

- *hwzweck* - *Hauptwegezweck* (primary trip purpose)
  - 1: Arbeit (work): assigned to *w04* value 1
  - 2: dienstlich (business): assigned to *w04* value 2 comprising occasional business trips as well as all rbW-trips
  - 3: Ausbildung (education): combines *w04* values 3, 31, 32
  - 4: Einkauf (purchasing: assigned to *w04* value 4
  - 5: Erledigung (errand): assigned to *w04* value 5
  - 6: Freizeit (leisure): combines *w04* values 7 and 10
  - 7: Begleitung (accompanying): combines *w04* values 6 and 11
  - 99: keine Angabe (not specified): combines *w04* values 97 and 98

Note, that all entries with *w04* values 8 or 9 were assigned to the primary trip purpose of the previous trip. In case the respective entry was the first trip on a working day (Monday – Friday) executed by a person older than 18 years, the trip was assigned to the primary trip purpose value 1, otherwise (on Saturdays or Sundays) to the value 6. Was it a person under 14 years the entry was assigned to the primary trip purpose value 7 and for persons between 14 or 18 years to the value 6. (Follmer et al., 2010*j*, p. 4)

A.2 Brown-Forsythe test tables

A.2.1 Household level

Table 12: Household level (Brown-Forsythe test): variance homogeneity of number of cars

	Dependent variable	Factor	df	n	F	$p_{adj.}$
1	number of cars	household type	10	44273	248.91	0.0e+00***
2	number of cars	economic status	4	44473	142.74	3.7e-121***
3	number of cars	place of residence	2	44492	237.17	3.5e-103***
4	number of cars, ln	household type	10	44273	206.09	0.0e+00***
5	number of cars, ln	economic status	4	44473	163.13	1.4e-138***
6	number of cars, ln	place of residence	2	44492	45.00	3.0e-20***
7	number of cars, reciprocal	household type	10	44273	473.41	0.0e+00***
8	number of cars, reciprocal	economic status	4	44473	247.88	1.1e-210***
9	number of cars, reciprocal	place of residence	2	44492	53.90	4.2e-24***
10	number of cars, sqrt	household type	10	44273	305.37	0.0e+00***
11	number of cars, sqrt	economic status	4	44473	187.32	3.3e-159***
12	number of cars, sqrt	place of residence	2	44492	19.72	2.8e-09***

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
Logarithmic transformation: $Y_{trans.} = ln(Y + 1)$
Reciprocal transformation: $Y_{trans.} = \frac{1}{Y+1}$
Square root transformation: $Y_{trans.} = \sqrt{Y}$

A.2.2 Vehicle level

Table 13: Vehicle level (Brown-Forsythe test): variance homogeneity of number of trips per (use) day

	Dependent variable	Factor	df	n	F	$p_{adj.}$
1	number of trips per day	weekday	2	34598	438.87	4.8e-188***
2	number of trips per day	household type	10	34435	26.28	1.2e-49***
3	number of trips per day	household type, combined	1	34444	217.93	2.2e-48***
4	number of trips per day	vehicle use freq.	2	17005	104.41	4.3e-45***
5	number of trips per day	occupation	6	25427	35.08	6.7e-42***
6	number of trips per day	economic status	4	34596	4.47	3.9e-03**
7	number of trips per day	season	3	31708	4.32	9.5e-03**
8	number of trips per day	place of residence	2	34598	3.60	2.7e-02*
9	number of trips per day, ln	weekday	2	34598	217.80	8.0e-94***
10	number of trips per day, ln	vehicle use freq.	2	17005	65.20	4.3e-28***
11	number of trips per day, ln	occupation	6	25427	21.23	3.2e-24***
12	number of trips per day, ln	household type	10	34435	6.35	3.9e-09***
13	number of trips per day, ln	household type, combined	1	34444	14.45	5.8e-04***
14	number of trips per day, ln	economic status	4	34596	5.63	4.8e-04***
15	number of trips per day, ln	place of residence	2	34598	7.96	7.0e-04***
16	number of trips per day, ln	season	3	31708	2.76	4.0e-02*
17	number of trips per day, reciprocal	vehicle use freq.	2	17005	125.87	4.4e-54***
18	number of trips per day, reciprocal	household type	10	34435	26.63	2.3e-50***
19	number of trips per day, reciprocal	household type, combined	1	34444	184.21	4.5e-41***
20	number of trips per day, reciprocal	occupation	6	25427	27.67	2.0e-32***
21	number of trips per day, reciprocal	weekday	2	34598	70.32	1.3e-30***
22	number of trips per day, reciprocal	place of residence	2	34598	21.93	9.1e-10***
23	number of trips per day, reciprocal	economic status	4	34596	9.92	1.0e-07***
24	number of trips per day, reciprocal	season	3	31708	2.39	6.7e-02
25	number of trips per day, sqrt	weekday	2	34598	176.33	5.1e-76***
26	number of trips per day, sqrt	vehicle use freq.	2	17005	66.14	1.7e-28***
27	number of trips per day, sqrt	occupation	6	25427	21.53	1.3e-24***
28	number of trips per day, sqrt	household type	10	34435	6.96	2.7e-10***
29	number of trips per day, sqrt	household type, combined	1	34444	17.36	1.2e-04***
30	number of trips per day, sqrt	economic status	4	34596	6.03	2.3e-04***
31	number of trips per day, sqrt	place of residence	2	34598	7.85	7.8e-04***
32	number of trips per day, sqrt	season	3	31708	2.72	4.3e-02*

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
Logarithmic transformation: $Y_{trans.} = ln(Y + 1)$
Reciprocal transformation: $Y_{trans.} = \frac{1}{Y+1}$
Square root transformation: $Y_{trans.} = \sqrt{Y}$

A.2.3 Trip level

Table 14: Trip level (Brown-Forsythe test): variance homogeneity of departure time [5min]

	Dependent variable	Factor	df	n	F	$p_{adj.}$
1	departure time [5min]	trip purpose	6	69955	682.34	0.0e+00***
2	departure time [5min]	trip distance categ.	2	68718	444.77	7.2e-192***
3	departure time [5min]	occupation	6	53059	142.86	1.0e-179***
4	departure time [5min]	weekday	2	69967	195.42	9.3e-85***
5	departure time [5min]	number of trips per day	3	69966	85.71	7.2e-55***
6	departure time [5min]	season	3	69966	9.74	4.0e-06***
7	departure time [5min]	place of residence	2	69967	4.58	1.0e-02*
8	departure time [5min], ln	trip purpose	6	69955	638.28	0.0e+00***
9	departure time [5min], ln	trip distance categ.	2	68718	649.13	3.1e-279***
10	departure time [5min], ln	occupation	6	53059	77.66	2.5e-96***
11	departure time [5min], ln	number of trips per day	3	69966	98.38	6.1e-63***
12	departure time [5min], ln	weekday	2	69967	71.97	1.8e-31***
13	departure time [5min], ln	place of residence	2	69967	8.11	6.0e-04***
14	departure time [5min], ln	season	3	69966	1.92	1.2e-01
15	departure time [5min], reciprocal	trip purpose	6	69955	23.37	6.8e-27***
16	departure time [5min], reciprocal	trip distance categ.	2	68718	6.40	1.0e-02**
17	departure time [5min], reciprocal	occupation	6	53059	2.85	4.4e-02*
18	departure time [5min], reciprocal	weekday	2	69967	3.88	8.3e-02
19	departure time [5min], reciprocal	number of trips per day	3	69966	2.04	3.2e-01
20	departure time [5min], reciprocal	place of residence	2	69967	1.77	3.4e-01
21	departure time [5min], reciprocal	season	3	69966	1.25	2.9e-01
22	departure time [5min], sqrt	trip purpose	6	69955	884.23	0.0e+00***
23	departure time [5min], sqrt	trip distance categ.	2	68718	772.53	0.0e+00***
24	departure time [5min], sqrt	occupation	6	53059	125.46	1.7e-157***
25	departure time [5min], sqrt	number of trips per day	3	69966	126.08	7.5e-81***
26	departure time [5min], sqrt	weekday	2	69967	169.26	1.4e-73***
27	departure time [5min], sqrt	place of residence	2	69967	8.49	4.1e-04***
28	departure time [5min], sqrt	season	3	69966	6.05	4.1e-04***

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
Logarithmic transformation: $Y_{trans.} = ln(Y)$
Reciprocal transformation: $Y_{trans.} = \frac{1}{Y}$
Square root transformation: $Y_{trans.} = \sqrt{Y}$

Table 15: Trip level (Brown-Forsythe test): variance homogeneity of driven distance [km]

	Dependent variable	Factor	df	n	F	$p_{adj.}$
29	driven distance [km]	trip purpose	6	69955	273.04	0.0e+00***
30	driven distance [km]	trip distance categ.	2	68718	1130.02	0.0e+00***
31	driven distance [km]	number of trips per day	3	69966	487.22	1.1e-312***
32	driven distance [km]	weekday	2	69967	121.44	9.0e-53***
33	driven distance [km]	occupation	6	53059	18.81	1.6e-21***
34	driven distance [km]	place of residence	2	69967	15.48	3.8e-07***
35	driven distance [km]	season	3	69966	7.50	5.1e-05***
36	driven distance [km], ln	trip distance categ.	2	68718	560.27	3.1e-241***
37	driven distance [km], ln	trip purpose	6	69955	97.25	1.6e-121***
38	driven distance [km], ln	place of residence	2	69967	155.14	3.0e-67***
39	driven distance [km], ln	number of trips per day	3	69966	62.31	1.3e-39***
40	driven distance [km], ln	occupation	6	53059	15.56	1.9e-17***
41	driven distance [km], ln	weekday	2	69967	28.27	1.1e-12***
42	driven distance [km], ln	season	3	69966	0.69	5.6e-01
43	driven distance [km], reciprocal	trip purpose	6	69955	341.68	0.0e+00***
44	driven distance [km], reciprocal	trip distance categ.	2	68718	2395.04	0.0e+00***
45	driven distance [km], reciprocal	number of trips per day	3	69966	413.54	1.3e-265***
46	driven distance [km], reciprocal	place of residence	2	69967	59.35	7.0e-26***
47	driven distance [km], reciprocal	occupation	6	53059	18.62	2.8e-21***
48	driven distance [km], reciprocal	weekday	2	69967	14.67	8.5e-07***
49	driven distance [km], reciprocal	season	3	69966	4.99	1.8e-03**
50	driven distance [km], sqrt	number of trips per day	3	69966	639.83	0.0e+00***
51	driven distance [km], sqrt	trip purpose	6	69955	395.91	0.0e+00***
52	driven distance [km], sqrt	trip distance categ.	2	68718	2376.55	0.0e+00***
53	driven distance [km], sqrt	weekday	2	69967	114.59	8.3e-50***
54	driven distance [km], sqrt	occupation	6	53059	38.45	2.1e-46***
55	driven distance [km], sqrt	place of residence	2	69967	62.47	1.6e-27***
56	driven distance [km], sqrt	season	3	69966	8.33	1.6e-05***

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
Logarithmic transformation: $Y_{trans.} = ln(Y)$
Reciprocal transformation: $Y_{trans.} = \frac{1}{Y}$
Square root transformation: $Y_{trans.} = \sqrt{Y}$

Table 16: Trip level (Brown-Forsythe test): variance homogeneity of driving time [5min]

	Dependent variable	Factor	df	n	F	$p_{adj.}$
57	driving time [5min]	number of trips per day	3	69966	525.91	0.0e+00***
58	driving time [5min]	trip purpose	6	69955	277.82	0.0e+00***
59	driving time [5min]	trip distance categ.	2	68718	993.31	0.0e+00***
60	driving time [5min]	weekday	2	69967	112.14	9.6e-49***
61	driving time [5min]	occupation	6	53059	12.80	5.0e-14***
62	driving time [5min]	season	3	69966	4.09	1.3e-02*
63	driving time [5min]	place of residence	2	69967	4.90	7.4e-03**
64	driving time [5min], ln	trip distance categ.	2	68718	492.64	2.6e-212***
65	driving time [5min], ln	trip purpose	6	69955	128.14	4.0e-161***
66	driving time [5min], ln	number of trips per day	3	69966	154.95	2.1e-99***
67	driving time [5min], ln	place of residence	2	69967	85.89	2.2e-37***
68	driving time [5min], ln	weekday	2	69967	59.56	4.3e-26***
69	driving time [5min], ln	occupation	6	53059	6.38	2.0e-06***
70	driving time [5min], ln	season	3	69966	2.90	3.4e-02*
71	driving time [5min], reciprocal	trip purpose	6	69955	297.46	0.0e+00***
72	driving time [5min], reciprocal	trip distance categ.	2	68718	1218.55	0.0e+00***
73	driving time [5min], reciprocal	number of trips per day	3	69966	316.17	3.2e-203***
74	driving time [5min], reciprocal	place of residence	2	69967	269.56	9.6e-117***
75	driving time [5min], reciprocal	occupation	6	53059	16.68	7.6e-19***
76	driving time [5min], reciprocal	weekday	2	69967	28.83	6.1e-13***
77	driving time [5min], reciprocal	season	3	69966	8.49	1.2e-05***
78	driving time [5min], sqrt	number of trips per day	3	69966	565.18	0.0e+00***
79	driving time [5min], sqrt	trip purpose	6	69955	307.37	0.0e+00***
80	driving time [5min], sqrt	trip distance categ.	2	68718	1419.87	0.0e+00***
81	driving time [5min], sqrt	weekday	2	69967	107.49	9.8e-47***
82	driving time [5min], sqrt	occupation	6	53059	15.51	2.2e-17***
83	driving time [5min], sqrt	place of residence	2	69967	9.93	9.7e-05***
84	driving time [5min], sqrt	season	3	69966	3.09	2.6e-02*

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
Logarithmic transformation: $Y_{trans.} = ln(Y)$
Reciprocal transformation: $Y_{trans.} = \frac{1}{Y}$
Square root transformation: $Y_{trans.} = \sqrt{Y}$

Table 17: Trip level (Brown-Forsythe test): variance homogeneity of parking time [5min]

	Dependent variable	Factor	df	n	F	$p_{adj.}$
85	parking time [5min]	number of trips per day	3	49169	2741.02	0.0e+00***
86	parking time [5min]	trip purpose	6	49163	2340.18	0.0e+00***
87	parking time [5min]	trip distance categ.	2	48324	6830.75	0.0e+00***
88	parking time [5min]	occupation	6	37397	226.78	5.3e-285***
89	parking time [5min]	weekday	2	49170	187.55	2.2e-81***
90	parking time [5min]	place of residence	2	49170	5.78	6.2e-03**
91	parking time [5min]	season	3	49169	2.31	7.4e-02
92	parking time [5min], ln	trip purpose	6	49163	244.74	1.1e-308***
93	parking time [5min], ln	occupation	6	37397	52.28	1.1e-63***
94	parking time [5min], ln	weekday	2	49170	78.80	3.4e-34***
95	parking time [5min], ln	trip distance categ.	2	48324	67.12	3.1e-29***
96	parking time [5min], ln	number of trips per day	3	49169	10.28	2.8e-06***
97	parking time [5min], ln	place of residence	2	49170	2.01	2.7e-01
98	parking time [5min], ln	season	3	49169	0.95	4.1e-01
99	parking time [5min], reciprocal	number of trips per day	3	49169	718.52	0.0e+00***
100	parking time [5min], reciprocal	trip purpose	6	49163	2175.51	0.0e+00***
101	parking time [5min], reciprocal	trip distance categ.	2	48324	752.53	7.4e-322***
102	parking time [5min], reciprocal	occupation	6	37397	16.89	5.6e-19***
103	parking time [5min], reciprocal	season	3	49169	3.70	3.3e-02*
104	parking time [5min], reciprocal	place of residence	2	49170	2.89	1.1e-01
105	parking time [5min], reciprocal	weekday	2	49170	0.48	6.2e-01
106	parking time [5min], sqrt	number of trips per day	3	49169	1378.37	0.0e+00***
107	parking time [5min], sqrt	trip purpose	6	49163	510.65	0.0e+00***
108	parking time [5min], sqrt	trip distance categ.	2	48324	3711.96	0.0e+00***
109	parking time [5min], sqrt	occupation	6	37397	213.58	1.9e-268***
110	parking time [5min], sqrt	weekday	2	49170	191.61	3.9e-83***
111	parking time [5min], sqrt	place of residence	2	49170	4.90	1.5e-02*
112	parking time [5min], sqrt	season	3	49169	1.51	2.1e-01

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
Logarithmic transformation: $Y_{trans.} = ln(Y)$
Reciprocal transformation: $Y_{trans.} = \frac{1}{Y}$
Square root transformation: $Y_{trans.} = \sqrt{Y}$

A.3 Specified research questions and statistical hypotheses

A.3.1 Household level

HL-N1-1: Do households with higher incomes tend to have more cars available in comparison to households with lower incomes?

H_0: *The # of cars of households with a higher 'economic household status' does* <u>*not tend*</u> *to be higher than for households with a lower 'economic household status'.*

H_1: *The # of cars of households with a higher 'economic household status'* <u>*tends*</u> *to be higher than for households with a lower 'economic household status'.*

HL-N1-2: Do family households tend to have more cars available in comparison to non-family households?

H_0: *The # of cars of households with a family 'household type' does* <u>*not tend*</u> *to be higher than for households with a non-family 'household type'.*

H_1: *The # of cars of households with a family 'household type'* <u>*tends*</u> *to be higher than for households with a non-family 'household type'.*

HL-N1-3: Do households from rural areas tend to have more cars available than households from urban or city areas?

H_0: *The # of cars of households with a rural 'place of residence' does* <u>*not tend*</u> *to be higher than for households with an urban or city 'place of residence'.*

H_1: *The # of cars of households with a rural 'place of residence'* <u>*tends*</u> *to be higher than for households with an urban or city 'place of residence'.*

HL-C2-1: Is the household's type dependent on the household's place of residence?

H_0: *Households with a family 'household type'* <u>*are not*</u> *more likely located in a rural or urban 'place of residence' compared to non-family households.*

H_1: *Households with a family 'household type' <u>are</u> more likely located in a rural or urban 'place of residence' compared to non-family households.*

A.3.2 Vehicle level

VL-N1-1: Do primary drivers from households with a higher economic status tend to drive more trips per day in comparison to primary drivers from households with lower economic status?

H_0: The # of car trips per (use) day of primary drivers from households with a higher 'economic household status' does not tend to be higher than for primary drivers from households with a lower 'economic household status'. H_1: The # of car trips per (use) day of primary drivers from households with a higher 'economic household status' tends to be higher than for primary drivers from households with a lower 'economic household status'.

VL-N1-2: Do primary drivers from family households tend to drive more trips per day in comparison to primary drivers from non-family households?

H_0: The # of car trips per (use) day of primary drivers from households with a family 'household type' does not tend to be higher than for primary drivers from households with a non-family 'household type'.

H_1: The # of car trips per (use) day of primary drivers from households with a family 'household type' tends to be higher than for primary drivers from households with a non-family 'household type'.

VL-N1-3: Do primary drivers from rural households tend to drive more trips per day in comparison to primary drivers from households from urban or city areas?

H_0: The # of car trips per (use) day of primary drivers from households with a rural 'place of residence' does not tend to be higher than for primary drivers from households with a an urban or city 'place of residence'.

H_1: The # of car trips per (use) day of primary drivers from households with a rural 'place of residence' tends to be higher than for primary drivers from households with an urban or city 'place of residence'.

VL-N1-4: Do primary drivers occupied as homemakers tend to drive more trips per day in comparison to primary drivers otherwise occupied?

H_0: *The # of car trips per (use) day of primary drivers with a homemaker 'main user occupation' does not tend to be higher than for primary drivers with a non-homemaker 'main user occupation'.*

H_1: *The # of car trips per (use) day of primary drivers with a homemaker 'main user occupation' tends to be higher than for primary drivers with a non-homemaker 'main user occupation'.*

VL-N1-5: Do primary drivers with a higher vehicle use frequency tend to drive more trips per day in comparison to primary drivers with a lower vehicle use frequency?

H_0: *The # of car trips per (use) day of primary drivers with a higher 'vehicle use frequency' does not tend to be higher than for primary drivers with a lower 'vehicle use frequency'.*

H_1: *The # of car trips per (use) day of primary drivers with a higher 'vehicle use frequency' tends to be higher than for primary drivers with a lower 'vehicle use frequency'.*

VL-N1-6: Do primary drivers tend to drive more trips per day in wintertime than in the other seasons?

H_0: *The # of car trips per (use) day of primary drivers does not tend to be higher in winter than in other 'seasons'.*

H_1: *The # of car trips per (use) day of primary drivers tends to be higher in winter than in other 'seasons'.*

VL-N1-7: Do primary drivers tend to drive more trips per day on workdays than on the other days of the week?

H_0: *The # of car trips per (use) day of primary drivers does not tend to be higher on workdays than on other 'weekdays'.*

H_1: *The # of car trips per (use) day of primary drivers tends to be higher on workdays than on other 'weekdays'.*

VL-C1-1: Is the main user's occupation dependent on the main user's household type?

H_0: *The attribute 'main user occupation' is independent from the attribute 'household type'*

H_1: *The attribute 'main user occupation' is dependent on the attribute 'household type'*

VL-C2-1: Is the main user's (vehicle) use frequency dependent on the main user's household type?

H_0: *The attribute 'main user (vehicle) use frequency' is independent from the attribute 'household type'.*

H_1: *The attribute 'main user (vehicle) use frequency' is dependent on the attribute 'household type'.*

VL-C2-2: Is the main user's (vehicle) use frequency dependent on the main user's occupation?

H_0: *The attribute 'main user (vehicle) use frequency' is independent from the attribute 'main user occupation'.*

H_1: *The attribute 'main user (vehicle) use frequency' is dependent on the attribute 'main user occupation'.*

VL-C2-3: Is the main user's (vehicle) use frequency dependent on the main user's place of residence?

H_0: *The attribute 'main user (vehicle) use frequency' is* <u>*independent*</u> *from the attribute 'place of residence'.*

H_1: *The attribute 'main user (vehicle) use frequency' is* <u>*dependent*</u> *on the attribute 'place of residence'.*

VL-C3-1: Is the main user's (daily vehicle) use dependent on the main user's (vehicle) use frequency?

H_0: *The attribute 'main user (daily vehicle) use' is* <u>*independent*</u> *from the attribute 'main user (vehicle) use frequency'.*

H_1: *The attribute 'main user (daily vehicle) use' is* <u>*dependent*</u> *on the attribute 'main user (vehicle) use frequency'.*

VL-C3-2: Is the main user's (daily vehicle) use dependent on the main user's place of residence?

H_0: *The attribute 'main user (daily vehicle) use' is* <u>*independent*</u> *from the attribute 'place of residence'.*

H_1: *The attribute 'main user (daily vehicle) use' is* <u>*dependent*</u> *on the attribute 'place of residence'.*

VL-C3-3: Is the main user's (daily vehicle) use dependent on the weekday of the vehicle use?

H_0: *The attribute 'main user (daily vehicle) use' is* <u>*independent*</u> *from the attribute 'weekday'.*

H_1: *The attribute 'main user (daily vehicle) use' is* <u>*dependent*</u> *on the attribute 'weekday'.*

A.3.3 Trip level

TL-N1-1: Do primary drivers who are occupied full-time tend to drive longer distances to work (or from work home) compared to primary drivers who are otherwise occupied?

H_0: *The driven distance to work (or from work home) of primary drivers with a full-time 'main user occupation' does not tend to be longer than for a primary driver with a non-fulltime 'main user occupation'.*

H_1: *The driven distance to work (or from work home) of primary drivers with a full-time 'main user occupation' tends to be longer than for a primary driver with a non-fulltime 'main user occupation'.*

TL-N1-2: Do primary drivers of rural households tend to drive longer distances to work (or from work home) compared to primary drivers from urban or city households?

H_0: *The driven distance to work (or from work home) of primary drivers from households with a rural 'place of residence' does not tend to be longer than for a primary driver from households with a urban or city 'place of residence'.*

H_1: *The driven distance to work (or from work home) of primary drivers from households with a rural 'place of residence' tends to be longer than for a primary driver from households with a urban or city 'place of residence'.*

TL-N2-1: Do leisure trips tend to have a longer driven distance compared to trips with other trip purposes?

H_0: *The driven distance of trips with a leisure 'trip purpose' does not tend to be longer than for trips with other 'trip purposes'.*

H_1: *The driven distance of trips with a leisure 'trip purpose' tends to be longer than for trips with other 'trip purposes'.*

TL-N2-2: Do outside city trips tend to have a longer driven distance compared to inside city trips?

H_0: The driven distance of trips with an outside city 'trip distance category' does <u>not tend</u> to be longer than for trips with an inside city or unknown 'trip distance category'.

H_1: The driven distance of trips with an outside city 'trip distance category' <u>tends</u> to be longer than for trips with an inside city or unknown 'trip distance category'.

TL-N2-3: Do trips driven on a day with multiple other trips tend to have a longer driven distance compared to trips driven on a day with fewer trips per (use) day?

H_0: The driven distance of trips driven on a day with only one or two 'trips per day' does <u>not tend</u> to be longer than for trips driven on a day with another 'number of trips per day'.

H_1: The driven distance of trips driven on a day with only one or two 'trips per day' <u>tends</u> to be longer than for trips driven on a day with another 'number of trips per day'.

TL-N2-4: Do trips driven on a workday tend to have a shorter driven distance compared to trips driven on a Saturday or Sunday?

H_0: The driven distance does <u>not tend</u> to be shorter for trips driven on workdays than on other 'weekdays'.

H_1: The driven distance <u>tends</u> to be shorter for trips driven on workdays than on other 'weekdays'.

TL-N2-5: Do trips driven in wintertime tend to have a longer driven distance compared to trips driven in other seasons?

H_0: The driven distance does <u>not tend</u> to be shorter for trips driven in winter than in other 'seasons'.

H_1: The driven distance <u>tends</u> to be shorter for trips driven in winter than in other 'seasons'.

TL-N3-1: Do primary drivers who are occupied full-time tend to depart earlier to work on their first trip of the day compared to primary drivers who are otherwise occupied?

H_0: *The departure time to work (of the first trip per day) of primary drivers with a fulltime 'main user occupation' does* <u>*not tend*</u> *to be earlier than for primary drivers with a non-fulltime 'main user occupation'.*

H_1: *The departure time to work (of the first trip per day) of primary drivers with a fulltime 'main user occupation'* <u>*tends*</u> *to be earlier than for primary drivers with a non-fulltime 'main user occupation'.*

TL-N3-2: Do primary drivers of rural households tend to depart earlier to work on their first trip of the day compared to primary drivers from urban or city households?

H_0: *The departure time to work (of the first trip per day) of primary drivers with a rural 'place of residence' does* <u>*not tend*</u> *to be earlier than for primary drivers with an urban or city 'place of residence'.*

H_0: *The departure time to work (of the first trip per day) of primary drivers with a rural 'place of residence'* <u>*tends*</u> *to be earlier than for primary drivers with an urban or city 'place of residence'.*

TL-N3-3: Do trips to work driven on a workday tend to have an earlier first departure time per day compared to trips to work driven on a Saturday or Sunday?

H_0: *The departure time to work (of the first trip per day) of trips driven on a workday does* <u>*not tend*</u> *to be earlier than for trips driven on a Saturday or Sunday.*

H_1: *The departure time to work (of the first trip per day) of trips driven on a workday* <u>*tends*</u> *to be earlier than for trips driven on a Saturday or Sunday.*

TL-N3-4: Do trips to work driven in wintertime tend to have an earlier first departure time per day compared to trips to work driven in other seasons?

H_0: The departure time to work (of the first trip per day) does not tend to be earlier for trips driven in winter than in other 'seasons'.

H_1: The departure time to work (of the first trip per day) tends to be earlier for trips driven in winter than in other 'seasons'.

TL-N4-1: Do leisure trips tend to have a later first departure time per day compared to trips with other trip purposes?

H_0: The departure time (of the first trip per day) of trips with a leisure 'trip purpose' does not tend to be later than for trips with other 'trip purposes'.

H_1: The departure time (of the first trip per day) of trips with a leisure 'trip purpose' tends to be later than for trips with other 'trip purposes'.

TL-N4-2: Do trips driven on a day with multiple other trips tend to have an earlier first departure time per day compared to trips driven on a day with fewer trips?

H_0: The departure time (of the first trip per day) for trips driven on a day with only one or two 'trips per day' does not tend to be earlier than for trips driven on a day with a larger 'number of trips per day'.

H_1: The departure time (of the first trip per day) for trips driven on a day with only one or two 'trips per day' tends to be earlier than for trips driven on a day with a larger 'number of trips per day'.

TL-N4-3: Do trips driven on a workday tend to have an earlier first departure time per day compared to trips driven on Saturdays or Sundays?

H_0: The departure time (of the first trip per day) of trips driven on a workday does not tend to be earlier than for trips driven on a Saturday or Sunday.

H_1: The departure time (of the first trip per day) of trips driven on a workday tends to be earlier than for trips driven on a Saturday or Sunday.

TL-N4-4: Do trips driven by a primary driver from a rural household tend to have an earlier first departure time per day compared to trips driven by primary drivers from urban or city households?

H_0: *The departure time (of the first trip per day) of trips driven by a primary driver with a rural 'place of residence' does <u>not tend</u> to be earlier than for primary drivers with an urban or city 'place of residence'.*

H_1: *The departure time (of the first trip per day) of trips driven by a primary driver with a rural 'place of residence' <u>tends</u> to be earlier than for primary drivers with an urban or city 'place of residence'.*

TL-N4-5: Do trips driven in wintertime tend to have a later first departure time per day compared to trips driven in other seasons?

H_0: *The departure time (of the first trip per day) does <u>not tend</u> to be smaller for trips driven in winter than in other 'seasons'.*

H_1: *The departure time (of the first trip per day) <u>tends</u> to be later for trips driven in winter than in other 'seasons'.*

TL-N5-1: Do primary drivers who are occupied full-time tend to drive longer to work (or from work home) compared to primary drivers who are otherwise occupied?

H_0: *The driving time to work (or from work home) of primary drivers with a fulltime 'main user occupation' does <u>not tend</u> to be longer than for primary drivers with a non-fulltime 'main user occupation'.*

H_1: *The driving time to work (or from work home) of primary drivers with a fulltime 'main user occupation' <u>tends</u> to be longer than for primary drivers with a non-fulltime 'main user occupation'.*

TL-N5-2: Do primary drivers of rural households tend to drive longer to work (or from work home) compared to primary drivers from urban or city households?

H_0: The driving time to work (or from work home) of primary drivers with a rural 'place of residence' does <u>not tend</u> to be longer than for primary drivers with an urban or city 'place of residence'.

H_0: The driving time to work (or from work home) of primary drivers with a rural 'place of residence' <u>tends</u> to be longer than for primary drivers with an urban or city 'place of residence'.

TL-N5-3: Do trips to work (or from work home) driven on a workday tend to have a longer driving time compared to trips to work (or from work home) driven on a Saturday or Sunday?

H_0: The driving time to work (or from work home) of trips driven on a workday does <u>not tend</u> to be longer than for trips driven on a Saturday or Sunday.

H_1: The driving time to work (or from work home) of trips driven on a workday <u>tends</u> to be longer than for trips driven on a Saturday or Sunday.

TL-N5-4: Do trips to work (or from work home) driven in wintertime tend to have a longer driving time compared to trips to work driven in other seasons?

H_0: The driving time to work (or from work home) does <u>not tend</u> to be longer for trips driven in winter than in other 'seasons'.

H_1: The driving time to work (or from work home) <u>tends</u> to be longer for trips driven in winter than in other 'seasons'.

TL-N6-1: Do leisure trips tend to have a longer driving time compared to trips with other trip purposes?

H_0: The driving time of trips with a leisure 'trip purpose' does <u>not tend</u> to be longer than for trips with other 'trip purposes'.

H_1: The driving time of trips with a leisure 'trip purpose' <u>tends</u> to be longer than for trips with other 'trip purposes'.

TL-N6-2: Do outside city trips tend to have a longer driving time compared to inside city trips?

H_0: *The driving time of trips with an outside city 'trip distance category' does <u>not tend</u> to be longer than for trips with an inside city or unknown 'trip distance category'.*

H_1: *The driving time of trips with an outside city 'trip distance category' <u>tends</u> to be longer than for trips with an inside city or unknown 'trip distance category'.*

TL-N6-3: Do trips driven on a day with multiple other trips tend to have a smaller driving time compared to trips driven on a day with fewer trips per (use) day?

H_0: *The driving time of trips driven on a day with only one or two 'trips per day' does <u>not tend</u> to be longer than for trips driven on a day with another 'number of trips per day'.*

H_1: *The driving time of trips driven on a day with only one or two 'trips per day' <u>tends</u> to be longer than for trips driven on a day with another 'number of trips per day'.*

TL-N6-4: Do trips driven on a workday tend to have a shorter driving time compared to trips driven on a Saturday or Sunday?

H_0: *The driving time does <u>not tend</u> to be shorter for trips driven on workdays than on other 'weekdays'.*

H_1: *The driving time <u>tends</u> to be shorter for trips driven on workdays than on other 'weekdays'.*

TL-N6-5: Do trips driven in wintertime tend to have a shorter driving time compared to trips driven in other seasons?

H_0: *The driving time does <u>not tend</u> to be shorter for trips driven in winter than in other 'seasons'.*

H_1: The driving time <u>tends</u> to be shorter for trips driven in winter than in other 'seasons'.

TL-N7-1: Do primary drivers who are occupied full-time tend to park longer at work compared to primary drivers who are otherwise occupied?

H_0: The parking time at work of primary drivers with a fulltime 'main user occupation' does <u>not tend</u> to be longer than for primary drivers with a non-fulltime 'main user occupation'.

H_1: The parking time at work of primary drivers with a fulltime 'main user occupation' <u>tends</u> to be longer than for primary drivers with a non-fulltime 'main user occupation'.

TL-N7-2: Do trips to work driven on a workday tend to park longer at work compared to trips to work driven on a Saturday or Sunday?

H_0: The parking time at work of trips driven on a workday does <u>not tend</u> to be longer than for trips driven on a Saturday or Sunday.

H_1: The parking time at work of trips driven on a workday <u>tends</u> to be longer than for trips driven on a Saturday or Sunday.

TL-N8-1: Do leisure trips tend to have a longer parking time compared to trips with other trip purposes?

H_0: The parking time of trips with a leisure 'trip purpose' does <u>not tend</u> to be longer than for trips with other 'trip purposes'.

H_1: The parking time of trips with a leisure 'trip purpose' <u>tends</u> to be longer than for trips with other 'trip purposes'.

TL-N8-2: Do trips driven on a day with multiple other trips tend to have a parking time compared to trips driven on a day with fewer trips per (use) day?

H_0: *The parking time of trips driven on a day with only one or two 'trips per day' does* <u>*not tend*</u> *to be longer than for trips driven on a day with another 'number of trips per day'.*

H_1: *The parking time of trips driven on a day with only one or two 'trips per day'* <u>*tends*</u> *to be longer than for trips driven on a day with another 'number of trips per day'.*

TL-N8-3: Do trips driven on a workday tend to have a shorter parking time compared to trips driven on a Saturday or Sunday?

H_0: *The parking time does* <u>*not tend*</u> *to be shorter for trips driven on workdays than on other 'weekdays'.*

H_1: *The parking time* <u>*tends*</u> *to be shorter for trips driven on workdays than on other 'weekdays'.*

TL-N8-4: Do trips driven in wintertime tend to have a shorter parking time compared to trips driven in other seasons?

H_0: *The parking time does* <u>*not tend*</u> *to be shorter for trips driven in winter than in other 'seasons'.*

H_1: *The parking time* <u>*tends*</u> *to be shorter for trips driven in winter than in other 'seasons'.*

TL-C1-1: Is the trip's departure and arrival place dependent on the main user's occupation?

H_0: *The attribute 'from...to' is* <u>*independent*</u> *from the attribute 'main user occupation'.*

H_1: *The attribute 'from...to' is* <u>*dependent*</u> *on the attribute 'main user occupation'.*

TL-C1-2: Is the trip's departure and arrival place dependent on the trip index?

H_0: *The attribute 'from...to' is* <u>*independent*</u> *from the attribute 'trip index'.*

H_1: *The attribute 'from...to' is* <u>*dependent*</u> *on the attribute 'trip index'.*

TL-C1-3: Is the trip's departure and arrival place dependent on the trip's weekday?

H_0: *The attribute 'from...to' is* <u>*independent*</u> *from the attribute 'weekday'.*

H_1: *The attribute 'from...to' is* <u>*dependent*</u> *on the attribute 'weekday'.*

TL-C2-1: Is the trip's purpose dependent on the trip's departure and arrival place?

H_0: *The attribute 'trip purpose' is* <u>*independent*</u> *from the attribute 'from...to'.*

H_1: *The attribute 'trip purpose' is* <u>*dependent*</u> *on the attribute 'from...to'.*

A.4 Test tables for Cliff's Method

A.4.1 Household level

Table 18: Household level (Cliff's method): main effects on number of cars

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	veryhigh vs. verylow	2410	2564	1.80	0.93	0.22	1e-04***	[0.54, 0.58]	large
2	economic status	medium vs. verylow	10835	2564	1.27	0.93	0.37	2e-04***	[0.23, 0.27]	small
3	economic status	medium vs. veryhigh	10835	2410	1.27	1.80	0.68	3e-04***	[-0.37, -0.33]	medium
4	economic status	low vs. verylow	2644	2564	1.11	0.93	0.46	4e-04***	[0.06, 0.12]	negligible
5	economic status	low vs. veryhigh	2644	2410	1.11	1.80	0.71	5e-04***	[-0.45, -0.39]	medium
6	economic status	low vs. medium	2644	10835	1.11	1.27	0.57	6e-04***	[-0.16, -0.11]	small
7	economic status	high vs. verylow	7442	2564	1.56	0.93	0.29	7e-04***	[0.41, 0.44]	medium
8	economic status	high vs. veryhigh	7442	2410	1.56	1.80	0.58	8e-04***	[-0.18, -0.13]	small
9	economic status	high vs. medium	7442	10835	1.56	1.27	0.40	9e-04***	[0.18, 0.21]	small
10	economic status	high vs. low	7442	2644	1.56	1.11	0.35	1e-03***	[0.27, 0.32]	small
11	household type	3mA vs. SP	3312	510	2.12	0.81	0.12	4.0e-04***	[0.74, 0.78]	large
12	household type	2Ay60p vs. SP	5757	510	1.10	0.81	0.38	5.0e-04***	[0.21, 0.28]	small
13	household type	2Ay60p vs. 3mA	5757	3312	1.10	2.12	0.82	6.0e-04***	[-0.65, -0.61]	large
14	household type	2A1mCu14 vs. 2A1mCu18	2767	1772	1.67	1.78	0.53	6.0e-04***	[-0.09, -0.03]	negligible
15	household type	2Ay3060 vs. SP	4623	510	1.43	0.81	0.25	7.0e-04***	[0.47, 0.52]	medium
16	household type	2Ay3060 vs. 3mA	4623	3312	1.43	2.12	0.71	8.0e-04***	[-0.44, -0.40]	medium
17	household type	2Ay3060 vs. 2Ay60p	4623	5757	1.43	1.10	0.36	9.0e-04***	[0.26, 0.30]	small
18	household type	2Ay1830 vs. SP	833	510	1.24	0.81	0.33	1.0e-03***	[0.28, 0.38]	medium
19	household type	2Ay1830 vs. 3mA	833	3312	1.24	2.12	0.75	1.1e-03**	[-0.53, -0.47]	medium
20	household type	2Ay1830 vs. 2Ay60p	833	5757	1.24	1.10	0.44	1.2e-03**	[0.09, 0.17]	small
21	household type	2Ay1830 vs. 2Ay3060	833	4623	1.24	1.43	0.56	1.3e-03**	[-0.16, -0.08]	small
22	household type	2A1mCu6 vs. SP	1841	510	1.58	0.81	0.20	1.4e-03**	[0.56, 0.62]	large
23	household type	2A1mCu6 vs. 3mA	1841	3312	1.58	2.12	0.67	1.5e-03**	[-0.36, -0.31]	medium
24	household type	2A1mCu6 vs. 2Ay60p	1841	5757	1.58	1.10	0.30	1.6e-03**	[0.37, 0.42]	medium
25	household type	2A1mCu6 vs. 2Ay3060	1841	4623	1.58	1.43	0.44	1.7e-03**	[0.08, 0.14]	small
26	household type	2A1mCu6 vs. 2Ay1830	1841	833	1.58	1.24	0.39	1.8e-03**	[0.18, 0.27]	small
27	household type	2A1mCu18 vs. SP	1772	510	1.78	0.81	0.17	1.9e-03**	[0.63, 0.69]	large
28	household type	2A1mCu18 vs. 3mA	1772	3312	1.78	2.12	0.61	2.0e-03**	[-0.24, -0.18]	small
29	household type	2A1mCu18 vs. 2Ay60p	1772	5757	1.78	1.10	0.26	2.1e-03**	[0.46, 0.51]	medium
30	household type	2A1mCu18 vs. 2Ay3060	1772	4623	1.78	1.43	0.39	2.2e-03**	[0.20, 0.26]	small
31	household type	2A1mCu18 vs. 2Ay1830	1772	833	1.78	1.24	0.34	2.3e-03**	[0.29, 0.37]	medium
32	household type	2A1mCu18 vs. 2A1mCu6	1772	1841	1.78	1.58	0.44	2.4e-03**	[0.09, 0.16]	small
33	household type	2A1mCu14 vs. SP	2767	510	1.67	0.81	0.18	2.5e-03**	[0.62, 0.67]	large
34	household type	2A1mCu14 vs. 3mA	2767	3312	1.67	2.12	0.64	2.6e-03**	[-0.31, -0.25]	small
35	household type	2A1mCu14 vs. 2Ay60p	2767	5757	1.67	1.10	0.27	2.7e-03**	[0.43, 0.47]	medium
36	household type	2A1mCu14 vs. 2Ay3060	2767	4623	1.67	1.43	0.41	2.8e-03**	[0.15, 0.20]	small
37	household type	2A1mCu14 vs. 2Ay1830	2767	833	1.67	1.24	0.36	2.9e-03**	[0.24, 0.32]	small
38	household type	2A1mCu14 vs. 2A1mCu6	2767	1841	1.67	1.58	0.47	3.0e-03**	[0.04, 0.10]	negligible
39	household type	1A60p vs. SP	2355	510	0.54	0.81	0.63	3.1e-03**	[-0.30, -0.21]	small
40	household type	1A60p vs. 3mA	2355	3312	0.54	2.12	0.92	3.2e-03**	[-0.85, -0.82]	large
41	household type	1A60p vs. 2Ay60p	2355	5757	0.54	1.10	0.73	3.3e-03**	[-0.48, -0.44]	medium
42	household type	1A60p vs. 2Ay3060	2355	4623	0.54	1.43	0.82	3.4e-03**	[-0.66, -0.63]	large
43	household type	1A60p vs. 2Ay1830	2355	833	0.54	1.24	0.75	3.5e-03**	[-0.53, -0.45]	medium
44	household type	1A60p vs. 2A1mCu6	2355	1841	0.54	1.58	0.86	3.6e-03**	[-0.73, -0.70]	large
45	household type	1A60p vs. 2A1mCu18	2355	1772	0.54	1.78	0.88	3.7e-03**	[-0.78, -0.75]	large
46	household type	1A60p vs. 2A1mCu14	2355	2767	0.54	1.67	0.88	3.8e-03**	[-0.77, -0.74]	large
47	household type	1A3060 vs. 3mA	1707	3312	0.79	2.12	0.88	3.9e-03**	[-0.77, -0.74]	large
48	household type	1A3060 vs. 2Ay60p	1707	5757	0.79	1.10	0.63	4.0e-03**	[-0.29, -0.24]	small
49	household type	1A3060 vs. 2Ay3060	1707	4623	0.79	1.43	0.75	4.1e-03**	[-0.52, -0.48]	medium
50	household type	1A3060 vs. 2Ay1830	1707	833	0.79	1.24	0.67	4.2e-03**	[-0.38, -0.30]	medium
51	household type	1A3060 vs. 2A1mCu6	1707	1841	0.79	1.58	0.79	4.3e-03**	[-0.61, -0.56]	large
52	household type	1A3060 vs. 2A1mCu18	1707	1772	0.79	1.78	0.83	4.4e-03**	[-0.68, -0.63]	large
53	household type	1A3060 vs. 2A1mCu14	1707	2767	0.79	1.67	0.82	4.5e-03**	[-0.66, -0.62]	large
54	household type	1A3060 vs. 1A60p	1707	2355	0.79	0.54	0.39	4.6e-03**	[0.19, 0.25]	small
55	household type	1A1830 vs. SP	307	510	0.66	0.81	0.59	4.7e-03**	[-0.24, -0.10]	small
56	household type	1A1830 vs. 3mA	307	3312	0.66	2.12	0.90	4.8e-03**	[-0.82, -0.76]	large
57	household type	1A1830 vs. 2Ay60p	307	5757	0.66	1.10	0.69	4.9e-03**	[-0.44, -0.33]	medium
58	household type	1A1830 vs. 2Ay3060	307	4623	0.66	1.43	0.79	5.0e-03**	[-0.62, -0.53]	large
59	household type	1A1830 vs. 2Ay1830	307	833	0.66	1.24	0.71	5.1e-03**	[-0.48, -0.37]	medium
60	household type	1A1830 vs. 2A1mCu6	307	1841	0.66	1.58	0.83	5.2e-03**	[-0.69, -0.61]	large
61	household type	1A1830 vs. 2A1mCu18	307	1772	0.66	1.78	0.85	5.3e-03**	[-0.75, -0.67]	large
62	household type	1A1830 vs. 2A1mCu14	307	2767	0.66	1.67	0.85	5.4e-03**	[-0.73, -0.66]	large
63	household type	1A1830 vs. 1A3060	307	1707	0.66	0.79	0.57	5.5e-03**	[-0.19, -0.07]	small
64	household type	1A1830 vs. 1A60p	307	2355	0.66	0.54	0.46	2.2e-02*	[0.02, 0.14]	negligible
65	household type	1A3060 vs. SP	1707	510	0.79	0.81	0.52	1.5e-01	n/c	n/c
66	place of residence	rural vs. urban	6327	11578	1.44	1.48	0.52	1e-04***	[-0.05, -0.02]	negligible
67	place of residence	city vs. urban	8007	11578	1.10	1.48	0.63	2e-04***	[-0.27, -0.24]	small
68	place of residence	city vs. rural	8007	6327	1.10	1.44	0.61	3e-04***	[-0.24, -0.20]	small

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 19: Household level (Cliff's method): interaction effects on number of cars controlling for household type = 1A1830

	Controlling for household type = 1A1830									
	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	medium vs. verylow	101	49	0.92	0.20	0.18	7.0e-04***	[0.50, 0.76]	large
2	economic status	low vs. medium	89	101	0.38	0.92	0.74	8.0e-04***	[-0.60, -0.35]	medium
3	economic status	high vs. verylow	57	49	0.86	0.20	0.19	9.0e-04***	[0.44, 0.74]	large
4	economic status	high vs. low	57	89	0.86	0.38	0.28	1.0e-03***	[0.29, 0.58]	medium
5	economic status	veryhigh vs. verylow	11	49	1.55	0.20	0.21	2.4e-02*	[0.20, 0.81]	large
6	economic status	low vs. veryhigh	89	11	0.38	1.55	0.73	9.5e-02	n/c	n/c
7	economic status	low vs. verylow	89	49	0.38	0.20	0.42	1.3e-01	n/c	n/c
8	economic status	medium vs. veryhigh	101	11	0.92	1.55	0.54	7.2e-01	n/c	n/c
9	economic status	high vs. veryhigh	57	11	0.86	1.55	0.56	1.2e+00	n/c	n/c
10	economic status	high vs. medium	57	101	0.86	0.92	0.52	1.8e+00	n/c	n/c
11	place of residence	city vs. urban	141	113	0.47	0.85	0.64	3.0e-04***	[-0.39, -0.15]	small
12	place of residence	city vs. rural	141	53	0.47	0.77	0.63	1.6e-03**	[-0.41, -0.11]	small
13	place of residence	rural vs. urban	53	113	0.77	0.85	0.51	8.2e-01	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 20: Household level (Cliff's method): interaction effects on number of cars controlling for household type = 1A3060

	Controlling for household type = 1A3060									
	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	veryhigh vs. verylow	167	79	1.10	0.48	0.25	3.0e-04***	[0.37, 0.60]	medium
2	economic status	medium vs. verylow	575	79	0.80	0.48	0.36	4.0e-04***	[0.16, 0.40]	small
3	economic status	medium vs. veryhigh	575	167	0.80	1.10	0.62	5.0e-04***	[-0.31, -0.16]	small
4	economic status	low vs. veryhigh	242	167	0.45	1.10	0.76	6.0e-04***	[-0.60, -0.44]	large
5	economic status	low vs. medium	242	575	0.45	0.80	0.66	7.0e-04***	[-0.39, -0.24]	medium
6	economic status	high vs. verylow	639	79	0.88	0.48	0.32	8.0e-04***	[0.24, 0.48]	medium
7	economic status	high vs. veryhigh	639	167	0.88	1.10	0.58	9.0e-04***	[-0.24, -0.09]	small
8	economic status	high vs. low	639	242	0.88	0.45	0.30	1.0e-03***	[0.33, 0.46]	medium
9	economic status	high vs. medium	639	575	0.88	0.80	0.46	4.0e-03**	[0.03, 0.13]	negligible
10	economic status	low vs. verylow	242	79	0.45	0.48	0.51	6.8e-01	n/c	n/c
11	place of residence	city vs. urban	653	677	0.61	0.92	0.63	2.0e-04***	[-0.31, -0.22]	small
12	place of residence	city vs. rural	653	377	0.61	0.90	0.63	3.0e-04***	[-0.31, -0.20]	small
13	place of residence	rural vs. urban	377	677	0.90	0.92	0.50	7.7e-01	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 21: Household level (Cliff's method): interaction effects on number of cars controlling for household type = 1A60p

	Controlling for household type = 1A60p									
	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	veryhigh vs. verylow	128	67	0.91	0.25	0.20	3.0e-04***	[0.47, 0.70]	large
2	economic status	medium vs. verylow	1048	67	0.52	0.25	0.37	4.0e-04***	[0.15, 0.37]	small
3	economic status	high vs. veryhigh	604	128	0.73	0.91	0.58	4.0e-04***	[-0.24, -0.07]	small
4	economic status	medium vs. veryhigh	1048	128	0.52	0.91	0.67	5.0e-04***	[-0.42, -0.27]	medium
5	economic status	low vs. veryhigh	503	128	0.31	0.91	0.77	6.0e-04***	[-0.62, -0.46]	large
6	economic status	low vs. medium	503	1048	0.31	0.52	0.60	7.0e-04***	[-0.25, -0.15]	small
7	economic status	high vs. verylow	604	67	0.73	0.25	0.27	8.0e-04***	[0.34, 0.55]	medium
8	economic status	high vs. medium	604	1048	0.73	0.52	0.40	9.0e-04***	[0.14, 0.24]	small
9	economic status	high vs. low	604	503	0.73	0.31	0.30	1.0e-03***	[0.34, 0.45]	medium
10	economic status	low vs. verylow	503	67	0.31	0.25	0.47	3.1e-01	n/c	n/c
11	place of residence	city vs. urban	926	899	0.45	0.62	0.58	3.0e-04***	[-0.20, -0.11]	small
12	place of residence	city vs. rural	926	530	0.45	0.57	0.55	4.0e-04***	[-0.16, -0.05]	small
13	place of residence	rural vs. urban	530	899	0.57	0.62	0.53	5.4e-02	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 22: Household level (Cliff's method): interaction effects on number of cars controlling for household type = SP

	Controlling for household type = SP									
	Factor	Level_1 vs. level_2	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	veryhigh vs. verylow	10	140	1.10	0.59	0.27	6.0e-04***	[0.32, 0.59]	medium
2	economic status	medium vs. verylow	152	140	0.94	0.59	0.33	7.0e-04***	[0.24, 0.43]	medium
3	economic status	low vs. medium	138	152	0.74	0.94	0.60	8.0e-04***	[-0.28, -0.11]	small
4	economic status	high vs. verylow	70	140	1.09	0.59	0.30	9.0e-04***	[0.28, 0.50]	medium
5	economic status	high vs. low	70	138	1.09	0.74	0.37	1.0e-03***	[0.15, 0.37]	small
6	economic status	low vs. veryhigh	138	10	0.74	1.10	0.67	1.0e-03***	[-0.48, -0.17]	medium
7	economic status	low vs. verylow	138	140	0.74	0.59	0.43	4.0e-02*	[0.04, 0.25]	small
8	economic status	high vs. medium	70	152	1.09	0.94	0.46	2.6e-01	n/c	n/c
9	economic status	medium vs. veryhigh	152	10	0.94	1.10	0.58	3.6e-01	n/c	n/c
10	economic status	high vs. veryhigh	70	10	1.09	1.10	0.53	5.5e-01	n/c	n/c
11	place of residence	city vs. urban	176	222	0.63	0.94	0.64	2.0e-04***	[-0.36, -0.19]	small
12	place of residence	city vs. rural	176	112	0.63	0.86	0.61	3.0e-04***	[-0.32, -0.11]	small
13	place of residence	rural vs. urban	112	222	0.86	0.94	0.53	1.9e-01	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 23: Household level (Cliff's method): interaction effects on number of cars controlling for household type = 2Ay1830

	Controlling for household type = 2Ay1830									
	Factor	Level_1 vs. level_2	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	veryhigh vs. verylow	53	202	1.58	0.75	0.21	5.0e-04***	[0.43, 0.69]	large
2	economic status	medium vs. verylow	354	202	1.31	0.75	0.30	6.0e-04***	[0.31, 0.48]	medium
3	economic status	low vs. veryhigh	16	53	0.75	1.58	0.79	7.0e-04***	[-0.76, -0.31]	large
4	economic status	high vs. verylow	208	202	1.55	0.75	0.22	8.0e-04***	[0.48, 0.64]	large
5	economic status	high vs. medium	208	354	1.55	1.31	0.41	9.0e-04***	[0.10, 0.27]	small
6	economic status	high vs. low	208	16	1.55	0.75	0.21	1.0e-03***	[0.32, 0.75]	large
7	economic status	low vs. medium	16	354	0.75	1.31	0.70	1.2e-02*	[-0.60, -0.15]	medium
8	economic status	medium vs. veryhigh	354	53	1.31	1.58	0.61	1.8e-02*	[-0.36, -0.06]	small
9	economic status	low vs. verylow	16	202	0.75	0.75	0.49	9.3e-01	n/c	n/c
10	economic status	high vs. veryhigh	208	53	1.55	1.58	0.52	1.1e+00	n/c	n/c
11	place of residence	city vs. urban	336	313	0.93	1.47	0.70	2.0e-04***	[-0.46, -0.32]	medium
12	place of residence	city vs. rural	336	184	0.93	1.42	0.67	3.0e-04***	[-0.43, -0.25]	medium
13	place of residence	rural vs. urban	184	313	1.42	1.47	0.52	3.3e-01	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 24: Household level (Cliff's method): interaction effects on number of cars controlling for household type = 2Ay3060

	Controlling for household type = 2Ay3060									
	Factor	Level_1 vs. level_2	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	veryhigh vs. verylow	707	447	1.77	0.96	0.20	2e-04***	[0.55, 0.65]	large
2	economic status	medium vs. verylow	1901	447	1.34	0.96	0.35	3e-04***	[0.26, 0.35]	medium
3	economic status	medium vs. veryhigh	1901	707	1.34	1.77	0.68	4e-04***	[-0.39, -0.31]	medium
4	economic status	low vs. veryhigh	62	707	0.94	1.77	0.80	5e-04***	[-0.69, -0.49]	large
5	economic status	low vs. medium	62	1901	0.94	1.34	0.66	6e-04***	[-0.43, -0.18]	medium
6	economic status	high vs. verylow	1501	447	1.56	0.96	0.26	7e-04***	[0.43, 0.52]	medium
7	economic status	high vs. veryhigh	1501	707	1.56	1.77	0.58	8e-04***	[-0.21, -0.12]	small
8	economic status	high vs. medium	1501	1901	1.56	1.34	0.40	9e-04***	[0.16, 0.23]	small
9	economic status	high vs. low	1501	62	1.56	0.94	0.26	1e-03***	[0.36, 0.58]	medium
10	economic status	low vs. verylow	62	447	0.94	0.96	0.51	8e-01	n/c	n/c
11	place of residence	city vs. urban	1319	2096	1.28	1.51	0.60	2.0e-04***	[-0.23, -0.16]	small
12	place of residence	city vs. rural	1319	1208	1.28	1.47	0.58	3.0e-04***	[-0.19, -0.11]	small
13	place of residence	rural vs. urban	1208	2096	1.47	1.51	0.52	1.7e-02*	[-0.08, -0.01]	negligible

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 25: Household level (Cliff's method): interaction effects on number of cars controlling for household type = 2Ay60p

Controlling for household type = 2Ay60p										
	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	veryhigh vs. verylow	383	906	1.57	0.87	0.23	2e-04***	[0.50, 0.60]	large
2	economic status	medium vs. verylow	3183	906	1.06	0.87	0.41	3e-04***	[0.14, 0.20]	small
3	economic status	medium vs. veryhigh	3183	383	1.06	1.57	0.71	4e-04***	[-0.48, -0.37]	medium
4	economic status	low vs. veryhigh	99	383	0.70	1.57	0.82	5e-04***	[-0.70, -0.56]	large
5	economic status	low vs. medium	99	3183	0.70	1.06	0.66	6e-04***	[-0.41, -0.23]	medium
6	economic status	high vs. verylow	1186	906	1.24	0.87	0.34	7e-04***	[0.28, 0.35]	medium
7	economic status	high vs. veryhigh	1186	383	1.24	1.57	0.64	8e-04***	[-0.33, -0.21]	small
8	economic status	high vs. medium	1186	3183	1.24	1.06	0.42	9e-04***	[0.13, 0.19]	small
9	economic status	high vs. low	1186	99	1.24	0.70	0.28	1e-03***	[0.36, 0.52]	medium
10	economic status	low vs. verylow	99	906	0.70	0.87	0.58	3e-03**	[-0.26, -0.06]	small
11	place of residence	rural vs. urban	1349	2359	1.07	1.16	0.54	2.0e-04***	[-0.11, -0.05]	negligible
12	place of residence	city vs. urban	2049	2359	1.03	1.16	0.56	3.0e-04***	[-0.14, -0.09]	small
13	place of residence	city vs. rural	2049	1349	1.03	1.07	0.52	1.6e-02*	[-0.07, -0.01]	negligible

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 26: Household level (Cliff's method): interaction effects on number of cars controlling for household type = 2A1mCu6

Controlling for household type = 2A1mCu6										
	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	veryhigh vs. verylow	202	129	1.82	1.15	0.26	4e-04***	[0.38, 0.58]	medium
2	economic status	medium vs. verylow	662	129	1.55	1.15	0.35	5e-04***	[0.21, 0.40]	medium
3	economic status	medium vs. veryhigh	662	202	1.55	1.82	0.60	6e-04***	[-0.28, -0.13]	small
4	economic status	low vs. veryhigh	260	202	1.39	1.82	0.67	7e-04***	[-0.42, -0.24]	medium
5	economic status	high vs. verylow	588	129	1.71	1.15	0.29	8e-04***	[0.33, 0.51]	medium
6	economic status	high vs. medium	588	662	1.71	1.55	0.43	9e-04***	[0.08, 0.19]	small
7	economic status	low vs. medium	260	662	1.39	1.55	0.57	9e-04***	[-0.21, -0.07]	small
8	economic status	high vs. low	588	260	1.71	1.39	0.36	1e-03***	[0.20, 0.34]	small
9	economic status	low vs. verylow	260	129	1.39	1.15	0.41	4e-03**	[0.07, 0.28]	small
10	economic status	high vs. veryhigh	588	202	1.71	1.82	0.54	7e-02	n/c	n/c
11	place of residence	city vs. urban	471	894	1.36	1.62	0.60	2.0e-04***	[-0.27, -0.15]	small
12	place of residence	city vs. rural	471	476	1.36	1.70	0.62	3.0e-04***	[-0.31, -0.18]	small
13	place of residence	rural vs. urban	476	894	1.70	1.62	0.48	1.2e-01	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 27: Household level (Cliff's method): interaction effects on number of cars controlling for household type = 2A1mCu14

Controlling for household type = 2A1mCu14										
	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	veryhigh vs. verylow	266	174	1.99	1.24	0.23	2e-04***	[0.45, 0.62]	large
2	economic status	medium vs. verylow	1057	174	1.65	1.24	0.34	3e-04***	[0.24, 0.40]	medium
3	economic status	medium vs. veryhigh	1057	266	1.65	1.99	0.63	4e-04***	[-0.33, -0.21]	small
4	economic status	low vs. verylow	408	174	1.45	1.24	0.42	4e-04***	[0.08, 0.26]	small
5	economic status	low vs. veryhigh	408	266	1.45	1.99	0.70	5e-04***	[-0.48, -0.34]	medium
6	economic status	low vs. medium	408	1057	1.45	1.65	0.58	6e-04***	[-0.22, -0.10]	small
7	economic status	high vs. verylow	861	174	1.79	1.24	0.29	7e-04***	[0.34, 0.50]	medium
8	economic status	high vs. veryhigh	861	266	1.79	1.99	0.58	8e-04***	[-0.22, -0.09]	small
9	economic status	high vs. medium	861	1057	1.79	1.65	0.44	9e-04***	[0.07, 0.16]	small
10	economic status	high vs. low	861	408	1.79	1.45	0.36	1e-03***	[0.21, 0.33]	small
11	place of residence	city vs. urban	614	1438	1.47	1.73	0.60	2.0e-04***	[-0.25, -0.15]	small
12	place of residence	city vs. rural	614	715	1.47	1.72	0.60	3.0e-04***	[-0.25, -0.14]	small
13	place of residence	rural vs. urban	715	1438	1.72	1.73	0.51	6.7e-01	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 28: Household level (Cliff's method): interaction effects on number of cars controlling for household type = 2A1mCu18

	Controlling for household type = 2A1mCu18									
	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	veryhigh vs. verylow	124	154	2.15	1.32	0.23	4.0e-04***	[0.43, 0.63]	large
2	economic status	medium vs. verylow	578	154	1.72	1.32	0.35	5.0e-04***	[0.20, 0.38]	small
3	economic status	medium vs. veryhigh	578	124	1.72	2.15	0.64	6.0e-04***	[-0.37, -0.19]	small
4	economic status	low vs. verylow	341	154	1.59	1.32	0.40	6.0e-04***	[0.10, 0.29]	small
5	economic status	low vs. veryhigh	341	124	1.59	2.15	0.69	7.0e-04***	[-0.46, -0.27]	medium
6	economic status	high vs. verylow	574	154	1.99	1.32	0.27	8.0e-04***	[0.36, 0.54]	medium
7	economic status	high vs. medium	574	578	1.99	1.72	0.40	9.0e-04***	[0.14, 0.25]	small
8	economic status	high vs. low	574	341	1.99	1.59	0.36	1.0e-03***	[0.21, 0.35]	small
9	economic status	low vs. medium	341	578	1.59	1.72	0.55	1.6e-02*	[-0.17, -0.03]	negligible
10	economic status	high vs. veryhigh	574	124	1.99	2.15	0.54	8.3e-02	n/c	n/c
11	place of residence	city vs. urban	420	925	1.54	1.83	0.60	2.0e-04***	[-0.26, -0.14]	small
12	place of residence	city vs. rural	420	427	1.54	1.91	0.62	3.0e-04***	[-0.31, -0.17]	small
13	place of residence	rural vs. urban	427	925	1.91	1.83	0.48	1.6e-01	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$ $\alpha_{CI} = 0.05$
Family-wise error rate correction method: Holm–Bonferroni Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
n/c: not calculated as p-value is not significant small: $0.1 \leq |\overline{CI}| < 0.3$
n/a: not available as $min(n_1, n_2) \leq 1$ medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 29: Household level (Cliff's method): interaction effects on number of cars controlling for household type = 3mA

	Controlling for household type = 3mA									
	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	veryhigh vs. verylow	350	203	2.53	1.52	0.23	3.0e-04***	[0.47, 0.62]	large
2	economic status	medium vs. verylow	1173	203	2.00	1.52	0.35	4.0e-04***	[0.22, 0.38]	medium
3	economic status	high vs. veryhigh	1123	350	2.32	2.53	0.56	4.0e-04***	[-0.19, -0.06]	small
4	economic status	medium vs. veryhigh	1173	350	2.00	2.53	0.66	5.0e-04***	[-0.37, -0.25]	medium
5	economic status	low vs. verylow	463	203	1.90	1.52	0.39	6.0e-04***	[0.14, 0.31]	small
6	economic status	low vs. veryhigh	463	350	1.90	2.53	0.67	7.0e-04***	[-0.40, -0.26]	medium
7	economic status	high vs. verylow	1123	203	2.32	1.52	0.27	8.0e-04***	[0.39, 0.54]	medium
8	economic status	high vs. medium	1123	1173	2.32	2.00	0.40	9.0e-04***	[0.15, 0.24]	small
9	economic status	high vs. low	1123	463	2.32	1.90	0.38	1.0e-03***	[0.18, 0.29]	small
10	economic status	low vs. medium	463	1173	1.90	2.00	0.53	6.2e-02	n/c	n/c
11	place of residence	city vs. urban	846	1593	1.74	2.26	0.65	2.0e-04***	[-0.34, -0.26]	medium
12	place of residence	city vs. rural	846	873	1.74	2.24	0.64	3.0e-04***	[-0.33, -0.24]	small
13	place of residence	rural vs. urban	873	1593	2.24	2.26	0.51	4.5e-01	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$ $\alpha_{CI} = 0.05$
Family-wise error rate correction method: Holm–Bonferroni Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
n/c: not calculated as p-value is not significant small: $0.1 \leq |\overline{CI}| < 0.3$
n/a: not available as $min(n_1, n_2) \leq 1$ medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 30: Household level (Cliff's method): interaction effects on number of cars controlling for place of residence = city

	Controlling for place of residence = city									
	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	veryhigh vs. verylow	878	706	1.58	0.65	0.20	2.0e-04***	[0.57, 0.64]	large
2	economic status	medium vs. verylow	3287	706	1.05	0.65	0.35	3.0e-04***	[0.27, 0.34]	medium
3	economic status	medium vs. veryhigh	3287	878	1.05	1.58	0.68	4.0e-04***	[-0.40, -0.33]	medium
4	economic status	low vs. veryhigh	740	878	0.73	1.58	0.77	5.0e-04***	[-0.59, -0.50]	large
5	economic status	low vs. medium	740	3287	0.73	1.05	0.63	6.0e-04***	[-0.30, -0.22]	small
6	economic status	high vs. verylow	2384	706	1.26	0.65	0.28	7.0e-04***	[0.39, 0.47]	medium
7	economic status	high vs. veryhigh	2384	878	1.26	1.58	0.61	8.0e-04***	[-0.25, -0.17]	small
8	economic status	high vs. medium	2384	3287	1.26	1.05	0.42	9.0e-04***	[0.13, 0.18]	small
9	economic status	high vs. low	2384	740	1.26	0.73	0.31	1.0e-03***	[0.34, 0.42]	medium
10	economic status	low vs. verylow	740	706	0.73	0.65	0.49	3.8e-01	n/c	n/c
11	household type	3mA vs. SP	846	176	1.74	0.63	0.16	1.0e-03***	[0.63, 0.72]	large
12	household type	2Ay60p vs. SP	2049	176	1.03	0.63	0.33	1.1e-03**	[0.27, 0.40]	medium
13	household type	2Ay60p vs. 3mA	2049	846	1.03	1.74	0.73	1.2e-03**	[-0.50, -0.42]	medium
14	household type	2Ay3060 vs. SP	1319	176	1.28	0.63	0.25	1.3e-03**	[0.44, 0.55]	medium
15	household type	2Ay3060 vs. 3mA	1319	846	1.28	1.74	0.65	1.4e-03**	[-0.34, -0.25]	small
16	household type	2Ay3060 vs. 2Ay60p	1319	2049	1.28	1.03	0.40	1.5e-03**	[0.17, 0.23]	small
17	household type	2Ay1830 vs. SP	336	176	0.93	0.63	0.40	1.6e-03**	[0.10, 0.28]	small
18	household type	2Ay1830 vs. 3mA	336	846	0.93	1.74	0.74	1.7e-03**	[-0.53, -0.42]	medium
19	household type	2Ay1830 vs. 2Ay3060	336	1319	0.93	1.28	0.63	1.8e-03**	[-0.32, -0.19]	small
20	household type	2A1mCu6 vs. SP	471	176	1.36	0.63	0.23	1.9e-03**	[0.47, 0.59]	large
21	household type	2A1mCu6 vs. 3mA	471	846	1.36	1.74	0.62	2.0e-03**	[-0.29, -0.18]	small
22	household type	2A1mCu6 vs. 2Ay60p	471	2049	1.36	1.03	0.37	2.1e-03**	[0.20, 0.31]	small
23	household type	2A1mCu6 vs. 2Ay1830	471	336	1.36	0.93	0.35	2.2e-03**	[0.23, 0.37]	small
24	household type	2A1mCu18 vs. SP	420	176	1.54	0.63	0.19	2.3e-03**	[0.55, 0.67]	large
25	household type	2A1mCu18 vs. 3mA	420	846	1.54	1.74	0.56	2.4e-03**	[-0.19, -0.07]	small
26	household type	2A1mCu18 vs. 2Ay60p	420	2049	1.54	1.03	0.32	2.5e-03**	[0.31, 0.41]	medium
27	household type	2A1mCu18 vs. 2Ay3060	420	1319	1.54	1.28	0.41	2.6e-03**	[0.12, 0.23]	small
28	household type	2A1mCu18 vs. 2Ay1830	420	336	1.54	0.93	0.30	2.7e-03**	[0.32, 0.46]	medium
29	household type	2A1mCu14 vs. SP	614	176	1.47	0.63	0.20	2.8e-03**	[0.55, 0.66]	large
30	household type	2A1mCu14 vs. 3mA	614	846	1.47	1.74	0.59	2.9e-03**	[-0.23, -0.12]	small
31	household type	2A1mCu14 vs. 2Ay60p	614	2049	1.47	1.03	0.33	3.0e-03**	[0.30, 0.39]	medium
32	household type	2A1mCu14 vs. 2Ay3060	614	1319	1.47	1.28	0.43	3.1e-03**	[0.09, 0.19]	small
33	household type	2A1mCu14 vs. 2Ay1830	614	336	1.47	0.93	0.32	3.2e-03**	[0.30, 0.43]	medium
34	household type	1A60p vs. SP	926	176	0.45	0.63	0.59	3.3e-03**	[-0.25, -0.09]	small
35	household type	1A60p vs. 3mA	926	846	0.45	1.74	0.87	3.4e-03**	[-0.77, -0.72]	large
36	household type	1A60p vs. 2Ay60p	926	2049	0.45	1.03	0.74	3.5e-03**	[-0.52, -0.45]	medium
37	household type	1A60p vs. 2Ay3060	926	1319	0.45	1.28	0.81	3.6e-03**	[-0.64, -0.58]	large
38	household type	1A60p vs. 2Ay1830	926	336	0.45	0.93	0.66	3.7e-03**	[-0.39, -0.26]	medium
39	household type	1A60p vs. 2A1mCu6	926	471	0.45	1.36	0.82	3.8e-03**	[-0.68, -0.59]	large
40	household type	1A60p vs. 2A1mCu18	926	420	0.45	1.54	0.85	3.9e-03**	[-0.74, -0.67]	large
41	household type	1A60p vs. 2A1mCu14	926	614	0.45	1.47	0.85	4.0e-03**	[-0.73, -0.67]	large
42	household type	1A3060 vs. 3mA	653	846	0.61	1.74	0.84	4.1e-03**	[-0.71, -0.64]	large
43	household type	1A3060 vs. 2Ay60p	653	2049	0.61	1.03	0.68	4.2e-03**	[-0.40, -0.32]	medium
44	household type	1A3060 vs. 2Ay3060	653	1319	0.61	1.28	0.75	4.3e-03**	[-0.54, -0.47]	large
45	household type	1A3060 vs. 2Ay1830	653	336	0.61	0.93	0.61	4.4e-03**	[-0.28, -0.14]	small
46	household type	1A3060 vs. 2A1mCu6	653	471	0.61	1.36	0.77	4.5e-03**	[-0.59, -0.49]	large
47	household type	1A3060 vs. 2A1mCu18	653	420	0.61	1.54	0.81	4.6e-03**	[-0.66, -0.57]	large
48	household type	1A3060 vs. 2A1mCu14	653	614	0.61	1.47	0.81	4.7e-03**	[-0.65, -0.57]	large
49	household type	1A3060 vs. 1A60p	653	926	0.61	0.45	0.43	4.8e-03**	[0.09, 0.19]	small
50	household type	1A1830 vs. 3mA	141	846	0.47	1.74	0.87	4.9e-03**	[-0.78, -0.70]	large
51	household type	1A1830 vs. 2Ay60p	141	2049	0.47	1.03	0.74	5.0e-03**	[-0.55, -0.40]	medium
52	household type	1A1830 vs. 2Ay3060	141	1319	0.47	1.28	0.80	5.1e-03**	[-0.66, -0.54]	large
53	household type	1A1830 vs. 2Ay1830	141	336	0.47	0.93	0.66	5.2e-03**	[-0.40, -0.22]	medium
54	household type	1A1830 vs. 2A1mCu6	141	471	0.47	1.36	0.82	5.3e-03**	[-0.69, -0.56]	large
55	household type	1A1830 vs. 2A1mCu18	141	420	0.47	1.54	0.85	5.4e-03**	[-0.75, -0.64]	large
56	household type	1A1830 vs. 2A1mCu14	141	614	0.47	1.47	0.85	5.5e-03**	[-0.75, -0.64]	large
57	household type	2A1mCu18 vs. 2A1mCu6	420	471	1.54	1.36	0.44	1.8e-02*	[0.04, 0.18]	small
58	household type	1A1830 vs. SP	141	176	0.47	0.63	0.58	4.8e-02*	[-0.27, -0.05]	small
59	household type	2Ay1830 vs. 2Ay60p	336	2049	0.93	1.03	0.55	5.4e-02	n/c	n/c
60	household type	1A1830 vs. 1A3060	141	653	0.47	0.61	0.56	6.3e-02	n/c	n/c
61	household type	2A1mCu14 vs. 2A1mCu6	614	471	1.47	1.36	0.46	8.0e-02	n/c	n/c
62	household type	2A1mCu6 vs. 2Ay3060	471	1319	1.36	1.28	0.47	1.0e-01	n/c	n/c
63	household type	1A1830 vs. 1A60p	141	926	0.47	0.45	0.49	7.2e-01	n/c	n/c
64	household type	2A1mCu14 vs. 2A1mCu18	614	420	1.47	1.54	0.52	8.1e-01	n/c	n/c
65	household type	1A3060 vs. SP	653	176	0.61	0.63	0.52	8.4e-01	n/c	n/c

Significance codes: $0.0 <$ p*** $\leq 0.001 <$ p** $\leq 0.01 <$ p* ≤ 0.05
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 31: Household level (Cliff's method): interaction effects on number of cars controlling for place of residence = rural

	Controlling for place of residence = rural									
	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	veryhigh vs. verylow	416	798	1.91	1.06	0.22	2e-04***	[0.50, 0.60]	large
2	economic status	medium vs. verylow	2816	798	1.37	1.06	0.38	3e-04***	[0.19, 0.27]	small
3	economic status	medium vs. veryhigh	2816	416	1.37	1.91	0.68	4e-04***	[-0.41, -0.31]	medium
4	economic status	low vs. veryhigh	718	416	1.24	1.91	0.70	5e-04***	[-0.46, -0.34]	medium
5	economic status	low vs. verylow	718	798	1.24	1.06	0.45	5e-04***	[0.04, 0.15]	negligible
6	economic status	low vs. medium	718	2816	1.24	1.37	0.55	6e-04***	[-0.15, -0.05]	small
7	economic status	high vs. verylow	1577	798	1.72	1.06	0.28	7e-04***	[0.41, 0.49]	medium
8	economic status	high vs. veryhigh	1577	416	1.72	1.91	0.56	8e-04***	[-0.18, -0.07]	small
9	economic status	high vs. medium	1577	2816	1.72	1.37	0.38	9e-04***	[0.21, 0.27]	small
10	economic status	high vs. low	1577	718	1.72	1.24	0.35	1e-03***	[0.25, 0.35]	medium
11	household type	3mA vs. SP	873	112	2.24	0.86	0.09	9.0e-04***	[0.77, 0.84]	large
12	household type	2Ay60p vs. SP	1349	112	1.07	0.86	0.41	1.0e-03***	[0.11, 0.26]	small
13	household type	2Ay60p vs. 3mA	1349	873	1.07	2.24	0.86	1.1e-03**	[-0.74, -0.68]	large
14	household type	2Ay3060 vs. SP	1208	112	1.47	0.86	0.25	1.2e-03**	[0.44, 0.55]	medium
15	household type	2Ay3060 vs. 3mA	1208	873	1.47	2.24	0.74	1.3e-03**	[-0.52, -0.44]	medium
16	household type	2Ay3060 vs. 2Ay60p	1208	1349	1.47	1.07	0.33	1.4e-03**	[0.29, 0.37]	medium
17	household type	2Ay1830 vs. SP	184	112	1.42	0.86	0.27	1.5e-03**	[0.35, 0.54]	medium
18	household type	2Ay1830 vs. 3mA	184	873	1.42	2.24	0.74	1.6e-03**	[-0.55, -0.42]	medium
19	household type	2A1mCu18 vs. 2A1mCu6	427	476	1.91	1.70	0.43	1.6e-03**	[0.06, 0.20]	small
20	household type	2Ay1830 vs. 2Ay60p	184	1349	1.42	1.07	0.35	1.7e-03**	[0.21, 0.38]	small
21	household type	2A1mCu6 vs. SP	476	112	1.70	0.86	0.18	1.8e-03**	[0.59, 0.70]	large
22	household type	2A1mCu6 vs. 3mA	476	873	1.70	2.24	0.67	1.9e-03**	[-0.39, -0.29]	medium
23	household type	2A1mCu6 vs. 2Ay60p	476	1349	1.70	1.07	0.25	2.0e-03**	[0.45, 0.54]	medium
24	household type	2A1mCu6 vs. 2Ay3060	476	1208	1.70	1.47	0.41	2.1e-03**	[0.12, 0.23]	small
25	household type	2A1mCu6 vs. 2Ay1830	476	184	1.70	1.42	0.41	2.2e-03**	[0.10, 0.27]	small
26	household type	2A1mCu18 vs. SP	427	112	1.91	0.86	0.15	2.3e-03**	[0.65, 0.75]	large
27	household type	2A1mCu18 vs. 3mA	427	873	1.91	2.24	0.60	2.4e-03**	[-0.27, -0.15]	small
28	household type	2A1mCu18 vs. 2Ay60p	427	1349	1.91	1.07	0.21	2.5e-03**	[0.53, 0.62]	large
29	household type	2A1mCu18 vs. 2Ay3060	427	1208	1.91	1.47	0.36	2.6e-03**	[0.23, 0.34]	small
30	household type	2A1mCu18 vs. 2Ay1830	427	184	1.91	1.42	0.35	2.7e-03**	[0.21, 0.38]	medium
31	household type	2A1mCu14 vs. SP	715	112	1.72	0.86	0.17	2.8e-03**	[0.60, 0.70]	large
32	household type	2A1mCu14 vs. 3mA	715	873	1.72	2.24	0.66	2.9e-03**	[-0.37, -0.27]	medium
33	household type	2A1mCu14 vs. 2Ay60p	715	1349	1.72	1.07	0.25	3.0e-03**	[0.47, 0.55]	large
34	household type	2A1mCu14 vs. 2Ay3060	715	1208	1.72	1.47	0.40	3.1e-03**	[0.15, 0.24]	small
35	household type	2A1mCu14 vs. 2Ay1830	715	184	1.72	1.42	0.40	3.2e-03**	[0.12, 0.29]	small
36	household type	1A60p vs. SP	530	112	0.57	0.86	0.64	3.3e-03**	[-0.36, -0.20]	small
37	household type	1A60p vs. 3mA	530	873	0.57	2.24	0.93	3.4e-03**	[-0.89, -0.84]	large
38	household type	1A60p vs. 2Ay60p	530	1349	0.57	1.07	0.72	3.5e-03**	[-0.48, -0.39]	medium
39	household type	1A60p vs. 2Ay3060	530	1208	0.57	1.47	0.82	3.6e-03**	[-0.68, -0.61]	large
40	household type	1A60p vs. 2Ay1830	530	184	0.57	1.42	0.80	3.7e-03**	[-0.67, -0.53]	large
41	household type	1A60p vs. 2A1mCu6	530	476	0.57	1.70	0.88	3.8e-03**	[-0.79, -0.72]	large
42	household type	1A60p vs. 2A1mCu18	530	427	0.57	1.91	0.90	3.9e-03**	[-0.83, -0.76]	large
43	household type	1A60p vs. 2A1mCu14	530	715	0.57	1.72	0.88	4.0e-03**	[-0.79, -0.73]	large
44	household type	1A3060 vs. 3mA	377	873	0.90	2.24	0.89	4.1e-03**	[-0.81, -0.75]	large
45	household type	1A3060 vs. 2Ay60p	377	1349	0.90	1.07	0.58	4.2e-03**	[-0.21, -0.11]	small
46	household type	2A1mCu14 vs. 2A1mCu18	715	427	1.72	1.91	0.56	4.2e-03**	[-0.17, -0.05]	small
47	household type	1A3060 vs. 2Ay3060	377	1208	0.90	1.47	0.73	4.3e-03**	[-0.50, -0.42]	medium
48	household type	1A3060 vs. 2Ay1830	377	184	0.90	1.42	0.71	4.4e-03**	[-0.50, -0.33]	medium
49	household type	1A3060 vs. 2A1mCu6	377	476	0.90	1.70	0.81	4.5e-03**	[-0.66, -0.56]	large
50	household type	1A3060 vs. 2A1mCu18	377	427	0.90	1.91	0.84	4.6e-03**	[-0.72, -0.63]	large
51	household type	1A3060 vs. 2A1mCu14	377	715	0.90	1.72	0.81	4.7e-03**	[-0.66, -0.58]	large
52	household type	1A3060 vs. 1A60p	377	530	0.90	0.57	0.36	4.8e-03**	[0.23, 0.35]	small
53	household type	1A1830 vs. 3mA	53	873	0.77	2.24	0.91	4.9e-03**	[-0.87, -0.73]	large
54	household type	1A1830 vs. 2Ay60p	53	1349	0.77	1.07	0.63	5.0e-03**	[-0.39, -0.14]	small
55	household type	1A1830 vs. 2Ay3060	53	1208	0.77	1.47	0.77	5.1e-03**	[-0.63, -0.43]	large
56	household type	1A1830 vs. 2Ay1830	53	184	0.77	1.42	0.75	5.2e-03**	[-0.60, -0.37]	medium
57	household type	1A1830 vs. 2A1mCu6	53	476	0.77	1.70	0.83	5.3e-03**	[-0.75, -0.57]	large
58	household type	1A1830 vs. 2A1mCu18	53	427	0.77	1.91	0.86	5.4e-03**	[-0.79, -0.63]	large
59	household type	1A1830 vs. 2A1mCu14	53	715	0.77	1.72	0.84	5.5e-03**	[-0.75, -0.58]	large
60	household type	1A1830 vs. 1A60p	53	530	0.77	0.57	0.41	6.6e-02	n/c	n/c
61	household type	1A1830 vs. 1A3060	53	377	0.77	0.90	0.56	4.8e-01	n/c	n/c
62	household type	1A3060 vs. SP	377	112	0.90	0.86	0.49	6.6e-01	n/c	n/c
63	household type	1A1830 vs. SP	53	112	0.77	0.86	0.55	8.0e-01	n/c	n/c
64	household type	2Ay1830 vs. 2Ay3060	184	1208	1.42	1.47	0.51	1.3e+00	n/c	n/c
65	household type	2A1mCu14 vs. 2A1mCu6	715	476	1.72	1.70	0.49	1.5e+00	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 32: Household level (Cliff's method): interaction effects on number of cars controlling for place of residence = urban

	Controlling for place of residence = urban									
	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	veryhigh vs. verylow	1116	1060	1.93	1.03	0.20	1e-04***	[0.56, 0.63]	large
2	economic status	medium vs. verylow	4732	1060	1.38	1.03	0.37	2e-04***	[0.23, 0.29]	small
3	economic status	medium vs. veryhigh	4732	1116	1.38	1.93	0.69	3e-04***	[-0.41, -0.34]	medium
4	economic status	low vs. verylow	1186	1060	1.28	1.03	0.43	4e-04***	[0.10, 0.19]	small
5	economic status	low vs. veryhigh	1186	1116	1.28	1.93	0.70	5e-04***	[-0.44, -0.37]	medium
6	economic status	low vs. medium	1186	4732	1.28	1.38	0.54	6e-04***	[-0.12, -0.05]	negligible
7	economic status	high vs. verylow	3481	1060	1.70	1.03	0.27	7e-04***	[0.43, 0.49]	medium
8	economic status	high vs. veryhigh	3481	1116	1.70	1.93	0.58	8e-04***	[-0.19, -0.13]	small
9	economic status	high vs. medium	3481	4732	1.70	1.38	0.39	9e-04***	[0.20, 0.24]	small
10	economic status	high vs. low	3481	1186	1.70	1.28	0.36	1e-03***	[0.24, 0.31]	small
11	household type	3mA vs. SP	1593	222	2.26	0.94	0.10	9.0e-04***	[0.76, 0.82]	large
12	household type	2Ay60p vs. SP	2359	222	1.16	0.94	0.39	1.0e-03***	[0.17, 0.26]	small
13	household type	2Ay60p vs. 3mA	2359	1593	1.16	2.26	0.84	1.1e-03**	[-0.70, -0.65]	large
14	household type	2Ay3060 vs. SP	2096	222	1.51	0.94	0.25	1.2e-03**	[0.45, 0.53]	medium
15	household type	2Ay3060 vs. 3mA	2096	1593	1.51	2.26	0.73	1.3e-03**	[-0.49, -0.43]	medium
16	household type	2Ay3060 vs. 2Ay60p	2096	2359	1.51	1.16	0.35	1.4e-03**	[0.27, 0.33]	medium
17	household type	2Ay1830 vs. SP	313	222	1.47	0.94	0.26	1.5e-03**	[0.41, 0.55]	medium
18	household type	2Ay1830 vs. 3mA	313	1593	1.47	2.26	0.74	1.6e-03**	[-0.52, -0.43]	medium
19	household type	2Ay1830 vs. 2Ay60p	313	2359	1.47	1.16	0.36	1.7e-03**	[0.22, 0.35]	small
20	household type	2A1mCu6 vs. SP	894	222	1.62	0.94	0.21	1.8e-03**	[0.54, 0.63]	large
21	household type	2A1mCu6 vs. 3mA	894	1593	1.62	2.26	0.70	1.9e-03**	[-0.44, -0.37]	medium
22	household type	2A1mCu6 vs. 2Ay60p	894	2359	1.62	1.16	0.30	2.0e-03**	[0.36, 0.43]	medium
23	household type	2A1mCu6 vs. 2Ay3060	894	2096	1.62	1.51	0.46	2.1e-03**	[0.05, 0.13]	negligible
24	household type	2A1mCu18 vs. SP	925	222	1.83	0.94	0.17	2.2e-03**	[0.61, 0.69]	large
25	household type	2A1mCu18 vs. 3mA	925	1593	1.83	2.26	0.63	2.3e-03**	[-0.31, -0.23]	small
26	household type	2A1mCu18 vs. 2Ay60p	925	2359	1.83	1.16	0.26	2.4e-03**	[0.45, 0.52]	medium
27	household type	2A1mCu14 vs. 2A1mCu6	1438	894	1.73	1.62	0.46	2.4e-03**	[0.04, 0.12]	negligible
28	household type	2A1mCu18 vs. 2Ay3060	925	2096	1.83	1.51	0.39	2.5e-03**	[0.17, 0.25]	small
29	household type	2A1mCu18 vs. 2Ay1830	925	313	1.83	1.47	0.39	2.6e-03**	[0.16, 0.28]	small
30	household type	2A1mCu18 vs. 2A1mCu6	925	894	1.83	1.62	0.43	2.7e-03**	[0.09, 0.18]	small
31	household type	2A1mCu14 vs. SP	1438	222	1.73	0.94	0.18	2.8e-03**	[0.60, 0.68]	large
32	household type	2A1mCu14 vs. 3mA	1438	1593	1.73	2.26	0.67	2.9e-03**	[-0.37, -0.30]	medium
33	household type	2A1mCu14 vs. 2Ay60p	1438	2359	1.73	1.16	0.27	3.0e-03**	[0.43, 0.49]	medium
34	household type	2A1mCu14 vs. 2Ay3060	1438	2096	1.73	1.51	0.42	3.1e-03**	[0.13, 0.19]	small
35	household type	2A1mCu14 vs. 2Ay1830	1438	313	1.73	1.47	0.41	3.2e-03**	[0.11, 0.23]	small
36	household type	1A60p vs. SP	899	222	0.62	0.94	0.64	3.3e-03**	[-0.34, -0.23]	small
37	household type	1A60p vs. 3mA	899	1593	0.62	2.26	0.93	3.4e-03**	[-0.88, -0.85]	large
38	household type	1A60p vs. 2Ay60p	899	2359	0.62	1.16	0.73	3.5e-03**	[-0.48, -0.42]	medium
39	household type	1A60p vs. 2Ay3060	899	2096	0.62	1.51	0.83	3.6e-03**	[-0.68, -0.63]	large
40	household type	1A60p vs. 2Ay1830	899	313	0.62	1.47	0.82	3.7e-03**	[-0.68, -0.58]	large
41	household type	1A60p vs. 2A1mCu6	899	894	0.62	1.62	0.86	3.8e-03**	[-0.75, -0.69]	large
42	household type	1A60p vs. 2A1mCu18	899	925	0.62	1.83	0.88	3.9e-03**	[-0.79, -0.74]	large
43	household type	1A60p vs. 2A1mCu14	899	1438	0.62	1.73	0.88	4.0e-03**	[-0.78, -0.74]	large
44	household type	1A3060 vs. 3mA	677	1593	0.92	2.26	0.89	4.1e-03**	[-0.80, -0.75]	large
45	household type	1A3060 vs. 2Ay60p	677	2359	0.92	1.16	0.61	4.2e-03**	[-0.26, -0.19]	small
46	household type	1A3060 vs. 2Ay3060	677	2096	0.92	1.51	0.75	4.3e-03**	[-0.52, -0.46]	medium
47	household type	1A3060 vs. 2Ay1830	677	313	0.92	1.47	0.74	4.4e-03**	[-0.54, -0.41]	medium
48	household type	1A3060 vs. 2A1mCu6	677	894	0.92	1.62	0.79	4.5e-03**	[-0.61, -0.54]	large
49	household type	1A3060 vs. 2A1mCu18	677	925	0.92	1.83	0.82	4.6e-03**	[-0.67, -0.60]	large
50	household type	1A3060 vs. 2A1mCu14	677	1438	0.92	1.73	0.81	4.7e-03**	[-0.66, -0.59]	large
51	household type	1A3060 vs. 1A60p	677	899	0.92	0.62	0.37	4.8e-03**	[0.21, 0.29]	small
52	household type	1A1830 vs. 3mA	113	1593	0.85	2.26	0.89	4.9e-03**	[-0.83, -0.71]	large
53	household type	1A1830 vs. 2Ay60p	113	2359	0.85	1.16	0.65	5.0e-03**	[-0.40, -0.21]	medium
54	household type	1A1830 vs. 2Ay3060	113	2096	0.85	1.51	0.76	5.1e-03**	[-0.60, -0.44]	large
55	household type	1A1830 vs. 2Ay1830	113	313	0.85	1.47	0.75	5.2e-03**	[-0.59, -0.41]	large
56	household type	1A1830 vs. 2A1mCu6	113	894	0.85	1.62	0.80	5.3e-03**	[-0.67, -0.51]	large
57	household type	1A1830 vs. 2A1mCu18	113	925	0.85	1.83	0.83	5.4e-03**	[-0.72, -0.58]	large
58	household type	1A1830 vs. 2A1mCu14	113	1438	0.85	1.73	0.82	5.5e-03**	[-0.71, -0.56]	large
59	household type	2A1mCu6 vs. 2Ay1830	894	313	1.62	1.47	0.45	2.1e-02*	[0.03, 0.17]	small
60	household type	1A1830 vs. 1A60p	113	899	0.85	0.62	0.43	4.2e-02*	[0.04, 0.24]	small
61	household type	2A1mCu14 vs. 2A1mCu18	1438	925	1.73	1.83	0.53	4.5e-02*	[-0.10, -0.02]	negligible
62	household type	1A1830 vs. SP	113	222	0.85	0.94	0.57	8.8e-02	n/c	n/c
63	household type	1A1830 vs. 1A3060	113	677	0.85	0.92	0.55	1.8e-01	n/c	n/c
64	household type	1A3060 vs. SP	677	222	0.92	0.94	0.52	6.0e-01	n/c	n/c
65	household type	2Ay1830 vs. 2Ay3060	313	2096	1.47	1.51	0.51	6.6e-01	n/c	n/c

Significance codes: 0.0 < p*** ≤ 0.001 < p** ≤ 0.01 < p* ≤ 0.05
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 33: Household level (Cliff's method): interaction effects on number of cars controlling for economic status = verylow

	Controlling for economic status = verylow									
	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	household type	3mA vs. SP	203	140	1.52	0.59	0.21	1.6e-03**	[0.49, 0.65]	large
2	household type	2Ay60p vs. SP	906	140	0.87	0.59	0.37	1.7e-03**	[0.17, 0.33]	small
3	household type	2Ay60p vs. 3mA	906	203	0.87	1.52	0.71	1.8e-03**	[-0.50, -0.33]	medium
4	household type	2Ay3060 vs. SP	447	140	0.96	0.59	0.35	1.9e-03**	[0.22, 0.39]	medium
5	household type	2Ay3060 vs. 3mA	447	203	0.96	1.52	0.68	2.0e-03**	[-0.43, -0.26]	medium
6	household type	2Ay1830 vs. 3mA	202	203	0.75	1.52	0.73	2.1e-03**	[-0.55, -0.37]	medium
7	household type	2Ay1830 vs. 2Ay3060	202	447	0.75	0.96	0.59	2.2e-03**	[-0.27, -0.10]	small
8	household type	2A1mCu6 vs. SP	129	140	1.15	0.59	0.28	2.3e-03**	[0.32, 0.53]	medium
9	household type	2A1mCu6 vs. 2Ay60p	129	906	1.15	0.87	0.39	2.4e-03**	[0.13, 0.32]	small
10	household type	2A1mCu6 vs. 2Ay1830	129	202	1.15	0.75	0.35	2.5e-03**	[0.20, 0.41]	medium
11	household type	2A1mCu18 vs. SP	154	140	1.32	0.59	0.25	2.6e-03**	[0.41, 0.59]	large
12	household type	2A1mCu18 vs. 2Ay60p	154	906	1.32	0.87	0.34	2.7e-03**	[0.22, 0.40]	medium
13	household type	2A1mCu18 vs. 2Ay3060	154	447	1.32	0.96	0.38	2.8e-03**	[0.14, 0.33]	small
14	household type	2A1mCu18 vs. 2Ay1830	154	202	1.32	0.75	0.31	2.9e-03**	[0.28, 0.48]	medium
15	household type	2A1mCu14 vs. SP	174	140	1.24	0.59	0.27	3.0e-03**	[0.36, 0.55]	medium
16	household type	2A1mCu6 vs. 3mA	129	203	1.15	1.52	0.61	3.0e-03**	[-0.33, -0.11]	small
17	household type	2A1mCu14 vs. 2Ay60p	174	906	1.24	0.87	0.37	3.1e-03**	[0.18, 0.34]	small
18	household type	2A1mCu14 vs. 2Ay3060	174	447	1.24	0.96	0.41	3.2e-03**	[0.10, 0.27]	small
19	household type	2A1mCu14 vs. 2Ay1830	174	202	1.24	0.75	0.33	3.3e-03**	[0.24, 0.43]	medium
20	household type	1A60p vs. SP	67	140	0.25	0.59	0.67	3.4e-03**	[-0.46, -0.20]	medium
21	household type	1A60p vs. 3mA	67	203	0.25	1.52	0.88	3.5e-03**	[-0.82, -0.67]	large
22	household type	1A60p vs. 2Ay60p	67	906	0.25	0.87	0.79	3.6e-03**	[-0.67, -0.46]	large
23	household type	1A60p vs. 2Ay3060	67	447	0.25	0.96	0.80	3.7e-03**	[-0.69, -0.49]	large
24	household type	1A60p vs. 2Ay1830	67	202	0.25	0.75	0.69	3.8e-03**	[-0.49, -0.26]	medium
25	household type	1A60p vs. 2A1mCu6	67	129	0.25	1.15	0.84	3.9e-03**	[-0.77, -0.57]	large
26	household type	1A60p vs. 2A1mCu18	67	154	0.25	1.32	0.86	4.0e-03**	[-0.81, -0.63]	large
27	household type	1A60p vs. 2A1mCu14	67	174	0.25	1.24	0.85	4.1e-03**	[-0.78, -0.60]	large
28	household type	1A3060 vs. 3mA	79	203	0.48	1.52	0.81	4.2e-03**	[-0.71, -0.53]	large
29	household type	1A3060 vs. 2Ay60p	79	906	0.48	0.87	0.68	4.3e-03**	[-0.47, -0.24]	medium
30	household type	1A3060 vs. 2Ay3060	79	447	0.48	0.96	0.70	4.4e-03**	[-0.51, -0.29]	medium
31	household type	1A3060 vs. 2A1mCu6	79	129	0.48	1.15	0.76	4.5e-03**	[-0.62, -0.38]	large
32	household type	1A3060 vs. 2A1mCu18	79	154	0.48	1.32	0.79	4.6e-03**	[-0.67, -0.46]	large
33	household type	1A3060 vs. 2A1mCu14	79	174	0.48	1.24	0.77	4.7e-03**	[-0.64, -0.42]	large
34	household type	1A1830 vs. SP	49	140	0.20	0.59	0.69	4.8e-03**	[-0.52, -0.24]	medium
35	household type	1A1830 vs. 3mA	49	203	0.20	1.52	0.89	4.9e-03**	[-0.85, -0.69]	large
36	household type	1A1830 vs. 2Ay60p	49	906	0.20	0.87	0.81	5.0e-03**	[-0.72, -0.50]	large
37	household type	1A1830 vs. 2Ay3060	49	447	0.20	0.96	0.82	5.1e-03**	[-0.73, -0.52]	large
38	household type	1A1830 vs. 2Ay1830	49	202	0.20	0.75	0.71	5.2e-03**	[-0.54, -0.30]	medium
39	household type	1A1830 vs. 2A1mCu6	49	129	0.20	1.15	0.86	5.3e-03**	[-0.81, -0.60]	large
40	household type	1A1830 vs. 2A1mCu18	49	154	0.20	1.32	0.88	5.4e-03**	[-0.84, -0.65]	large
41	household type	1A1830 vs. 2A1mCu14	49	174	0.20	1.24	0.87	5.5e-03**	[-0.82, -0.62]	large
42	household type	2A1mCu14 vs. 3mA	174	203	1.24	1.52	0.59	2.8e-02*	[-0.28, -0.07]	small
43	household type	1A1830 vs. 1A3060	49	79	0.20	0.48	0.63	3.9e-02*	[-0.41, -0.09]	small
44	household type	2Ay1830 vs. 2Ay60p	202	906	0.75	0.87	0.57	4.0e-02*	[-0.22, -0.04]	small
45	household type	2A1mCu6 vs. 2Ay3060	129	447	1.15	0.96	0.43	4.4e-02*	[0.05, 0.24]	small
46	household type	1A3060 vs. 2Ay1830	79	202	0.48	0.75	0.60	4.8e-02*	[-0.31, -0.06]	small
47	household type	2Ay3060 vs. 2Ay60p	447	906	0.96	0.87	0.46	7.2e-02	n/c	n/c
48	household type	1A3060 vs. 1A60p	79	67	0.48	0.25	0.40	8.1e-02	n/c	n/c
49	household type	2A1mCu18 vs. 3mA	154	203	1.32	1.52	0.56	2.0e-01	n/c	n/c
50	household type	2A1mCu18 vs. 2A1mCu6	154	129	1.32	1.15	0.45	4.8e-01	n/c	n/c
51	household type	1A1830 vs. 1A60p	49	67	0.20	0.25	0.52	5.4e-01	n/c	n/c
52	household type	2Ay1830 vs. SP	202	140	0.75	0.59	0.46	5.5e-01	n/c	n/c
53	household type	1A3060 vs. SP	79	140	0.48	0.59	0.56	5.5e-01	n/c	n/c
54	household type	2A1mCu14 vs. 2A1mCu6	174	129	1.24	1.15	0.48	9.4e-01	n/c	n/c
55	household type	2A1mCu14 vs. 2A1mCu18	174	154	1.24	1.32	0.53	1.1e+00	n/c	n/c
56	place of residence	city vs. urban	706	1060	0.65	1.03	0.65	2.0e-04***	[-0.35, -0.26]	medium
57	place of residence	city vs. rural	706	798	0.65	1.06	0.65	3.0e-04***	[-0.36, -0.26]	medium
58	place of residence	rural vs. urban	798	1060	1.06	1.03	0.49	5.6e-01	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 34: Household level (Cliff's method): interaction effects on number of cars controlling for economic status = low

	Controlling for economic status = low									
	Factor	Level_1 vs. level_2	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	household type	3mA vs. SP	463	138	1.90	0.74	0.16	1.8e-03**	[0.62, 0.72]	large
2	household type	2Ay60p vs. 3mA	99	463	0.70	1.90	0.84	1.9e-03**	[-0.74, -0.62]	large
3	household type	2Ay3060 vs. 3mA	62	463	0.94	1.90	0.78	2.0e-03**	[-0.64, -0.45]	large
4	household type	2Ay1830 vs. 3mA	16	463	0.75	1.90	0.82	2.1e-03**	[-0.77, -0.43]	large
5	household type	2A1mCu6 vs. SP	260	138	1.39	0.74	0.25	2.2e-03**	[0.43, 0.57]	medium
6	household type	2A1mCu6 vs. 3mA	260	463	1.39	1.90	0.65	2.3e-03**	[-0.38, -0.23]	medium
7	household type	2A1mCu6 vs. 2Ay60p	260	99	1.39	0.70	0.24	2.4e-03**	[0.43, 0.60]	large
8	household type	2A1mCu6 vs. 2Ay3060	260	62	1.39	0.94	0.34	2.5e-03**	[0.19, 0.45]	medium
9	household type	2A1mCu18 vs. SP	341	138	1.59	0.74	0.20	2.6e-03**	[0.54, 0.66]	large
10	household type	2A1mCu18 vs. 3mA	341	463	1.59	1.90	0.59	2.7e-03**	[-0.26, -0.11]	small
11	household type	2A1mCu18 vs. 2Ay60p	341	99	1.59	0.70	0.19	2.8e-03**	[0.54, 0.68]	large
12	household type	2A1mCu18 vs. 2Ay3060	341	62	1.59	0.94	0.28	2.9e-03**	[0.32, 0.55]	medium
13	household type	2A1mCu18 vs. 2Ay1830	341	16	1.59	0.75	0.22	3.0e-03**	[0.30, 0.73]	large
14	household type	2A1mCu14 vs. SP	408	138	1.45	0.74	0.23	3.1e-03**	[0.47, 0.59]	large
15	household type	2A1mCu14 vs. 3mA	408	463	1.45	1.90	0.63	3.2e-03**	[-0.33, -0.20]	small
16	household type	2A1mCu14 vs. 2Ay60p	408	99	1.45	0.70	0.22	3.3e-03**	[0.47, 0.62]	large
17	household type	2A1mCu14 vs. 2Ay3060	408	62	1.45	0.94	0.31	3.4e-03**	[0.24, 0.49]	medium
18	household type	1A60p vs. SP	503	138	0.31	0.74	0.71	3.5e-03**	[-0.51, -0.34]	medium
19	household type	1A60p vs. 3mA	503	463	0.31	1.90	0.91	3.6e-03**	[-0.86, -0.79]	large
20	household type	1A60p vs. 2Ay60p	503	99	0.31	0.70	0.68	3.7e-03**	[-0.46, -0.26]	medium
21	household type	1A60p vs. 2Ay3060	503	62	0.31	0.94	0.76	3.8e-03**	[-0.62, -0.38]	large
22	household type	1A60p vs. 2A1mCu6	503	260	0.31	1.39	0.88	3.9e-03**	[-0.80, -0.72]	large
23	household type	1A60p vs. 2A1mCu18	503	341	0.31	1.59	0.91	4.0e-03**	[-0.85, -0.78]	large
24	household type	1A60p vs. 2A1mCu14	503	408	0.31	1.45	0.89	4.1e-03**	[-0.81, -0.74]	large
25	household type	1A3060 vs. SP	242	138	0.45	0.74	0.65	4.2e-03**	[-0.39, -0.20]	small
26	household type	1A3060 vs. 3mA	242	463	0.45	1.90	0.89	4.3e-03**	[-0.82, -0.73]	large
27	household type	1A3060 vs. 2Ay60p	242	99	0.45	0.70	0.62	4.4e-03**	[-0.35, -0.12]	small
28	household type	1A3060 vs. 2Ay3060	242	62	0.45	0.94	0.70	4.5e-03**	[-0.52, -0.26]	medium
29	household type	1A3060 vs. 2A1mCu6	242	260	0.45	1.39	0.84	4.6e-03**	[-0.73, -0.61]	large
30	household type	1A3060 vs. 2A1mCu18	242	341	0.45	1.59	0.87	4.7e-03**	[-0.79, -0.69]	large
31	household type	1A3060 vs. 2A1mCu14	242	408	0.45	1.45	0.85	4.8e-03**	[-0.75, -0.65]	large
32	household type	1A1830 vs. SP	89	138	0.38	0.74	0.68	4.9e-03**	[-0.48, -0.23]	medium
33	household type	1A1830 vs. 3mA	89	463	0.38	1.90	0.90	5.0e-03**	[-0.85, -0.74]	large
34	household type	1A1830 vs. 2Ay60p	89	99	0.38	0.70	0.65	5.1e-03**	[-0.43, -0.16]	small
35	household type	1A1830 vs. 2Ay3060	89	62	0.38	0.94	0.73	5.2e-03**	[-0.59, -0.30]	medium
36	household type	1A1830 vs. 2A1mCu6	89	260	0.38	1.39	0.86	5.3e-03**	[-0.78, -0.63]	large
37	household type	1A1830 vs. 2A1mCu18	89	341	0.38	1.59	0.89	5.4e-03**	[-0.83, -0.71]	large
38	household type	1A1830 vs. 2A1mCu14	89	408	0.38	1.45	0.87	5.5e-03**	[-0.80, -0.66]	large
39	household type	2A1mCu14 vs. 2Ay1830	408	16	1.45	0.75	0.26	8.5e-03**	[0.22, 0.69]	medium
40	household type	2A1mCu18 vs. 2A1mCu6	341	260	1.59	1.39	0.43	1.3e-02*	[0.06, 0.22]	small
41	household type	2A1mCu6 vs. 2Ay1830	260	16	1.39	0.75	0.27	2.8e-02*	[0.18, 0.66]	medium
42	household type	1A3060 vs. 1A60p	242	503	0.45	0.31	0.44	3.0e-02*	[0.05, 0.20]	small
43	household type	2A1mCu14 vs. 2A1mCu18	408	341	1.45	1.59	0.55	1.9e-01	n/c	n/c
44	household type	1A60p vs. 2Ay1830	503	16	0.31	0.75	0.68	2.1e-01	n/c	n/c
45	household type	2Ay3060 vs. 2Ay60p	62	99	0.94	0.70	0.40	2.1e-01	n/c	n/c
46	household type	1A1830 vs. 2Ay1830	89	16	0.38	0.75	0.65	4.7e-01	n/c	n/c
47	household type	2Ay3060 vs. SP	62	138	0.94	0.74	0.42	4.9e-01	n/c	n/c
48	household type	1A3060 vs. 2Ay1830	242	16	0.45	0.75	0.62	8.8e-01	n/c	n/c
49	household type	2Ay1830 vs. SP	16	138	0.75	0.74	0.51	9.0e-01	n/c	n/c
50	household type	2Ay1830 vs. 2Ay3060	16	62	0.75	0.94	0.58	1.3e+00	n/c	n/c
51	household type	2Ay60p vs. SP	99	138	0.70	0.74	0.53	1.3e+00	n/c	n/c
52	household type	2A1mCu14 vs. 2A1mCu6	408	260	1.45	1.39	0.47	1.5e+00	n/c	n/c
53	household type	1A1830 vs. 1A3060	89	242	0.38	0.45	0.53	1.6e+00	n/c	n/c
54	household type	1A1830 vs. 1A60p	89	503	0.38	0.31	0.47	1.6e+00	n/c	n/c
55	household type	2Ay1830 vs. 2Ay60p	16	99	0.75	0.70	0.49	1.8e+00	n/c	n/c
56	place of residence	city vs. urban	740	1186	0.73	1.28	0.67	2e-04***	[-0.39, -0.30]	medium
57	place of residence	city vs. rural	740	718	0.73	1.24	0.66	3e-04***	[-0.36, -0.26]	medium
58	place of residence	rural vs. urban	718	1186	1.24	1.28	0.51	3e-01	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 35: Household level (Cliff's method): interaction effects on number of cars controlling for economic status = medium

	Controlling for economic status = medium									
	Factor	Level_1 vs. level_2	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	household type	3mA vs. SP	1173	152	2.00	0.94	0.14	8.0e-04***	[0.68, 0.75]	large
2	household type	2Ay60p vs. SP	3183	152	1.06	0.94	0.45	9.0e-04***	[0.06, 0.16]	small
3	household type	2Ay60p vs. 3mA	3183	1173	1.06	2.00	0.82	1.0e-03***	[-0.66, -0.60]	large
4	household type	2Ay3060 vs. SP	1901	152	1.34	0.94	0.33	1.1e-03**	[0.30, 0.39]	medium
5	household type	2Ay3060 vs. 3mA	1901	1173	1.34	2.00	0.72	1.2e-03**	[-0.48, -0.41]	medium
6	household type	2Ay3060 vs. 2Ay60p	1901	3183	1.34	1.06	0.38	1.3e-03**	[0.22, 0.27]	small
7	household type	2Ay1830 vs. SP	354	152	1.31	0.94	0.34	1.4e-03**	[0.24, 0.39]	medium
8	household type	2A1mCu18 vs. 2A1mCu6	578	662	1.72	1.55	0.44	1.4e-03**	[0.06, 0.17]	small
9	household type	2Ay1830 vs. 3mA	354	1173	1.31	2.00	0.71	1.5e-03**	[-0.47, -0.37]	medium
10	household type	2Ay1830 vs. 2Ay60p	354	3183	1.31	1.06	0.39	1.6e-03**	[0.15, 0.28]	small
11	household type	2A1mCu6 vs. SP	662	152	1.55	0.94	0.24	1.7e-03**	[0.47, 0.57]	large
12	household type	2A1mCu6 vs. 3mA	662	1173	1.55	2.00	0.65	1.8e-03**	[-0.35, -0.26]	medium
13	household type	2A1mCu6 vs. 2Ay60p	662	3183	1.55	1.06	0.29	1.9e-03**	[0.37, 0.45]	medium
14	household type	2A1mCu6 vs. 2Ay3060	662	1901	1.55	1.34	0.41	2.0e-03**	[0.13, 0.22]	small
15	household type	2A1mCu6 vs. 2Ay1830	662	354	1.55	1.31	0.42	2.1e-03**	[0.09, 0.23]	small
16	household type	2A1mCu18 vs. SP	578	152	1.72	0.94	0.20	2.2e-03**	[0.54, 0.64]	large
17	household type	2A1mCu18 vs. 3mA	578	1173	1.72	2.00	0.59	2.3e-03**	[-0.24, -0.14]	small
18	household type	2A1mCu18 vs. 2Ay60p	578	3183	1.72	1.06	0.25	2.4e-03**	[0.45, 0.54]	medium
19	household type	2A1mCu18 vs. 2Ay3060	578	1901	1.72	1.34	0.36	2.5e-03**	[0.23, 0.32]	small
20	household type	2A1mCu18 vs. 2Ay1830	578	354	1.72	1.31	0.37	2.6e-03**	[0.19, 0.33]	small
21	household type	2A1mCu14 vs. SP	1057	152	1.65	0.94	0.21	2.7e-03**	[0.55, 0.63]	large
22	household type	2A1mCu14 vs. 3mA	1057	1173	1.65	2.00	0.62	2.8e-03**	[-0.28, -0.19]	small
23	household type	2A1mCu14 vs. 2Ay60p	1057	3183	1.65	1.06	0.26	2.9e-03**	[0.45, 0.52]	medium
24	household type	2A1mCu14 vs. 2Ay3060	1057	1901	1.65	1.34	0.38	3.0e-03**	[0.21, 0.29]	small
25	household type	2A1mCu14 vs. 2Ay1830	1057	354	1.65	1.31	0.38	3.1e-03**	[0.17, 0.29]	small
26	household type	1A60p vs. SP	1048	152	0.52	0.94	0.70	3.2e-03**	[-0.46, -0.35]	medium
27	household type	1A60p vs. 3mA	1048	1173	0.52	2.00	0.92	3.3e-03**	[-0.85, -0.81]	large
28	household type	1A60p vs. 2Ay60p	1048	3183	0.52	1.06	0.74	3.4e-03**	[-0.50, -0.44]	medium
29	household type	1A60p vs. 2Ay3060	1048	1901	0.52	1.34	0.81	3.5e-03**	[-0.65, -0.59]	large
30	household type	1A60p vs. 2Ay1830	1048	354	0.52	1.31	0.78	3.6e-03**	[-0.61, -0.51]	large
31	household type	1A60p vs. 2A1mCu6	1048	662	0.52	1.55	0.86	3.7e-03**	[-0.75, -0.69]	large
32	household type	1A60p vs. 2A1mCu18	1048	578	0.52	1.72	0.88	3.8e-03**	[-0.80, -0.74]	large
33	household type	1A60p vs. 2A1mCu14	1048	1057	0.52	1.65	0.88	3.9e-03**	[-0.79, -0.75]	large
34	household type	1A3060 vs. SP	575	152	0.80	0.94	0.58	4.0e-03**	[-0.21, -0.09]	small
35	household type	1A3060 vs. 3mA	575	1173	0.80	2.00	0.87	4.1e-03**	[-0.77, -0.71]	large
36	household type	1A3060 vs. 2Ay60p	575	3183	0.80	1.06	0.62	4.2e-03**	[-0.28, -0.20]	small
37	household type	1A3060 vs. 2Ay3060	575	1901	0.80	1.34	0.72	4.3e-03**	[-0.48, -0.41]	medium
38	household type	1A3060 vs. 2Ay1830	575	354	0.80	1.31	0.70	4.4e-03**	[-0.46, -0.33]	medium
39	household type	1A3060 vs. 2A1mCu6	575	662	0.80	1.55	0.79	4.5e-03**	[-0.62, -0.54]	large
40	household type	1A3060 vs. 2A1mCu18	575	578	0.80	1.72	0.82	4.6e-03**	[-0.68, -0.61]	large
41	household type	1A3060 vs. 2A1mCu14	575	1057	0.80	1.65	0.82	4.7e-03**	[-0.67, -0.61]	large
42	household type	1A3060 vs. 1A60p	575	1048	0.80	0.52	0.38	4.8e-03**	[0.19, 0.29]	small
43	household type	1A1830 vs. 3mA	101	1173	0.92	2.00	0.85	4.9e-03**	[-0.75, -0.63]	large
44	household type	1A1830 vs. 2Ay3060	101	1901	0.92	1.34	0.68	5.0e-03**	[-0.43, -0.28]	medium
45	household type	1A1830 vs. 2Ay1830	101	354	0.92	1.31	0.66	5.1e-03**	[-0.41, -0.23]	medium
46	household type	1A1830 vs. 2A1mCu6	101	662	0.92	1.55	0.76	5.2e-03**	[-0.58, -0.43]	large
47	household type	1A1830 vs. 2A1mCu18	101	578	0.92	1.72	0.79	5.3e-03**	[-0.65, -0.51]	large
48	household type	1A1830 vs. 2A1mCu14	101	1057	0.92	1.65	0.79	5.4e-03**	[-0.64, -0.50]	large
49	household type	1A1830 vs. 1A60p	101	1048	0.92	0.52	0.32	5.5e-03**	[0.27, 0.43]	medium
50	household type	1A1830 vs. 2Ay60p	101	3183	0.92	1.06	0.57	1.2e-02*	[-0.22, -0.06]	small
51	household type	2A1mCu14 vs. 2A1mCu6	1057	662	1.65	1.55	0.46	1.5e-02*	[0.03, 0.13]	negligible
52	household type	1A1830 vs. 1A3060	101	575	0.92	0.80	0.45	7.2e-02	n/c	n/c
53	household type	2A1mCu14 vs. 2A1mCu18	1057	578	1.65	1.72	0.52	4.5e-01	n/c	n/c
54	household type	1A1830 vs. SP	101	152	0.92	0.94	0.52	8.6e-01	n/c	n/c
55	household type	2Ay1830 vs. 2Ay3060	354	1901	1.31	1.34	0.50	9.4e-01	n/c	n/c
56	place of residence	city vs. urban	3287	4732	1.05	1.38	0.62	2.0e-04***	[-0.26, -0.22]	small
57	place of residence	city vs. rural	3287	2816	1.05	1.37	0.61	3.0e-04***	[-0.25, -0.21]	small
58	place of residence	rural vs. urban	2816	4732	1.37	1.38	0.51	3.7e-01	n/c	n/c

Significance codes: 0.0 < p*** ≤ 0.001 < p** ≤ 0.01 < p* ≤ 0.05
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 36: Household level (Cliff's method): interaction effects on number of cars controlling for economic status = high

	Controlling for economic status = high									
	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	household type	3mA vs. SP	1123	70	2.32	1.09	0.12	9.0e-04***	[0.67, 0.83]	large
2	household type	2Ay60p vs. 3mA	1186	1123	1.24	2.32	0.83	1.0e-03***	[-0.69, -0.63]	large
3	household type	2Ay3060 vs. SP	1501	70	1.56	1.09	0.28	1.1e-03**	[0.35, 0.53]	medium
4	household type	2Ay3060 vs. 3mA	1501	1123	1.56	2.32	0.74	1.2e-03**	[-0.51, -0.44]	medium
5	household type	2Ay3060 vs. 2Ay60p	1501	1186	1.56	1.24	0.36	1.3e-03**	[0.24, 0.31]	small
6	household type	2Ay1830 vs. SP	208	70	1.55	1.09	0.28	1.4e-03**	[0.33, 0.55]	medium
7	household type	2Ay1830 vs. 3mA	208	1123	1.55	2.32	0.74	1.5e-03**	[-0.53, -0.42]	medium
8	household type	2Ay1830 vs. 2Ay60p	208	1186	1.55	1.24	0.36	1.6e-03**	[0.20, 0.36]	small
9	household type	2A1mCu6 vs. SP	588	70	1.71	1.09	0.23	1.7e-03**	[0.45, 0.64]	large
10	household type	2A1mCu6 vs. 3mA	588	1123	1.71	2.32	0.70	1.8e-03**	[-0.43, -0.35]	medium
11	household type	2A1mCu6 vs. 2Ay60p	588	1186	1.71	1.24	0.31	1.9e-03**	[0.34, 0.43]	medium
12	household type	2A1mCu6 vs. 2Ay3060	588	1501	1.71	1.56	0.44	2.0e-03**	[0.07, 0.16]	small
13	household type	2A1mCu18 vs. SP	574	70	1.99	1.09	0.17	2.1e-03**	[0.56, 0.74]	large
14	household type	2A1mCu18 vs. 3mA	574	1123	1.99	2.32	0.60	2.2e-03**	[-0.25, -0.15]	small
15	household type	2A1mCu18 vs. 2Ay60p	574	1186	1.99	1.24	0.24	2.3e-03**	[0.48, 0.57]	large
16	household type	2A1mCu18 vs. 2Ay3060	574	1501	1.99	1.56	0.35	2.4e-03**	[0.25, 0.35]	small
17	household type	2Ay60p vs. SP	1186	70	1.24	1.09	0.41	2.4e-03**	[0.08, 0.27]	small
18	household type	2A1mCu18 vs. 2Ay1830	574	208	1.99	1.55	0.35	2.5e-03**	[0.22, 0.37]	small
19	household type	2A1mCu18 vs. 2A1mCu6	574	588	1.99	1.71	0.40	2.6e-03**	[0.14, 0.25]	small
20	household type	2A1mCu14 vs. SP	861	70	1.79	1.09	0.20	2.7e-03**	[0.50, 0.68]	large
21	household type	2A1mCu14 vs. 3mA	861	1123	1.79	2.32	0.67	2.8e-03**	[-0.38, -0.30]	medium
22	household type	2A1mCu14 vs. 2Ay60p	861	1186	1.79	1.24	0.28	2.9e-03**	[0.40, 0.48]	medium
23	household type	2A1mCu14 vs. 2Ay3060	861	1501	1.79	1.56	0.41	3.0e-03**	[0.13, 0.22]	small
24	household type	2A1mCu14 vs. 2Ay1830	861	208	1.79	1.55	0.42	3.1e-03**	[0.09, 0.24]	small
25	household type	2A1mCu14 vs. 2A1mCu18	861	574	1.79	1.99	0.57	3.2e-03**	[-0.19, -0.08]	small
26	household type	1A60p vs. SP	604	70	0.73	1.09	0.64	3.3e-03**	[-0.36, -0.18]	small
27	household type	1A60p vs. 3mA	604	1123	0.73	2.32	0.93	3.4e-03**	[-0.88, -0.84]	large
28	household type	1A60p vs. 2Ay60p	604	1186	0.73	1.24	0.71	3.5e-03**	[-0.45, -0.38]	medium
29	household type	1A60p vs. 2Ay3060	604	1501	0.73	1.56	0.82	3.6e-03**	[-0.66, -0.60]	large
30	household type	1A60p vs. 2Ay1830	604	208	0.73	1.55	0.81	3.7e-03**	[-0.69, -0.56]	large
31	household type	1A60p vs. 2A1mCu6	604	588	0.73	1.71	0.86	3.8e-03**	[-0.75, -0.67]	large
32	household type	1A60p vs. 2A1mCu18	604	574	0.73	1.99	0.90	3.9e-03**	[-0.82, -0.76]	large
33	household type	1A60p vs. 2A1mCu14	604	861	0.73	1.79	0.87	4.0e-03**	[-0.78, -0.72]	large
34	household type	1A3060 vs. 3mA	639	1123	0.88	2.32	0.91	4.1e-03**	[-0.85, -0.80]	large
35	household type	1A3060 vs. 2Ay60p	639	1186	0.88	1.24	0.65	4.2e-03**	[-0.35, -0.27]	medium
36	household type	1A3060 vs. 2Ay3060	639	1501	0.88	1.56	0.78	4.3e-03**	[-0.59, -0.52]	large
37	household type	1A3060 vs. 2Ay1830	639	208	0.88	1.55	0.78	4.4e-03**	[-0.62, -0.48]	large
38	household type	1A3060 vs. 2A1mCu6	639	588	0.88	1.71	0.82	4.5e-03**	[-0.69, -0.60]	large
39	household type	1A3060 vs. 2A1mCu18	639	574	0.88	1.99	0.87	4.6e-03**	[-0.77, -0.70]	large
40	household type	1A3060 vs. 2A1mCu14	639	861	0.88	1.79	0.84	4.7e-03**	[-0.72, -0.65]	large
41	household type	1A3060 vs. 1A60p	639	604	0.88	0.73	0.43	4.8e-03**	[0.08, 0.18]	small
42	household type	1A1830 vs. 3mA	57	1123	0.86	2.32	0.92	4.9e-03**	[-0.88, -0.78]	large
43	household type	1A1830 vs. 2Ay60p	57	1186	0.86	1.24	0.66	5.0e-03**	[-0.41, -0.21]	medium
44	household type	1A1830 vs. 2Ay3060	57	1501	0.86	1.56	0.78	5.1e-03**	[-0.64, -0.48]	large
45	household type	1A1830 vs. 2Ay1830	57	208	0.86	1.55	0.78	5.2e-03**	[-0.65, -0.46]	large
46	household type	1A1830 vs. 2A1mCu6	57	588	0.86	1.71	0.83	5.3e-03**	[-0.72, -0.57]	large
47	household type	1A1830 vs. 2A1mCu18	57	574	0.86	1.99	0.87	5.4e-03**	[-0.80, -0.68]	large
48	household type	1A1830 vs. 2A1mCu14	57	861	0.86	1.79	0.85	5.5e-03**	[-0.76, -0.62]	large
49	household type	1A3060 vs. SP	639	70	0.88	1.09	0.57	2.1e-02*	[-0.23, -0.05]	small
50	household type	2A1mCu6 vs. 2Ay1830	588	208	1.71	1.55	0.44	4.2e-02*	[0.03, 0.19]	small
51	household type	2A1mCu14 vs. 2A1mCu6	861	588	1.79	1.71	0.47	1.2e-01	n/c	n/c
52	household type	1A1830 vs. SP	57	70	0.86	1.09	0.58	1.4e-01	n/c	n/c
53	household type	1A1830 vs. 1A60p	57	604	0.86	0.73	0.44	1.4e-01	n/c	n/c
54	household type	2Ay1830 vs. 2Ay3060	208	1501	1.55	1.56	0.50	8.8e-01	n/c	n/c
55	household type	1A1830 vs. 1A3060	57	639	0.86	0.88	0.51	1.7e+00	n/c	n/c
56	place of residence	city vs. urban	2384	3481	1.26	1.70	0.64	2.0e-04***	[-0.32, -0.26]	small
57	place of residence	city vs. rural	2384	1577	1.26	1.72	0.65	3.0e-04***	[-0.33, -0.27]	small
58	place of residence	rural vs. urban	1577	3481	1.72	1.70	0.49	4.4e-01	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 37: Household level (Cliff's method): interaction effects on number of cars per household controlling for economic status = veryhigh

	Controlling for economic status = veryhigh									
	Factor	Level_1 vs. level_2	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	household type	3mA vs. SP	350	10	2.53	1.10	0.09	2.3e-03**	[0.68, 0.89]	large
2	household type	2Ay60p vs. SP	383	10	1.57	1.10	0.29	2.4e-03**	[0.22, 0.59]	medium
3	household type	2Ay60p vs. 3mA	383	350	1.57	2.53	0.78	2.5e-03**	[-0.62, -0.50]	large
4	household type	2Ay3060 vs. SP	707	10	1.77	1.10	0.21	2.6e-03**	[0.38, 0.73]	large
5	household type	2Ay3060 vs. 3mA	707	350	1.77	2.53	0.73	2.7e-03**	[-0.52, -0.39]	medium
6	household type	2Ay3060 vs. 2Ay60p	707	383	1.77	1.57	0.42	2.8e-03**	[0.10, 0.22]	small
7	household type	2Ay1830 vs. 3mA	53	350	1.58	2.53	0.77	2.9e-03**	[-0.63, -0.43]	large
8	household type	2A1mCu6 vs. SP	202	10	1.82	1.10	0.20	3.0e-03**	[0.38, 0.76]	large
9	household type	2A1mCu6 vs. 3mA	202	350	1.82	2.53	0.72	3.1e-03**	[-0.51, -0.36]	medium
10	household type	2A1mCu6 vs. 2Ay60p	202	383	1.82	1.57	0.41	3.2e-03**	[0.10, 0.27]	small
11	household type	2A1mCu18 vs. SP	124	10	2.15	1.10	0.12	3.3e-03**	[0.54, 0.88]	large
12	household type	2A1mCu18 vs. 3mA	124	350	2.15	2.53	0.62	3.4e-03**	[-0.35, -0.14]	small
13	household type	2A1mCu18 vs. 2Ay60p	124	383	2.15	1.57	0.31	3.5e-03**	[0.28, 0.47]	medium
14	household type	2A1mCu18 vs. 2Ay3060	124	707	2.15	1.77	0.38	3.6e-03**	[0.14, 0.33]	small
15	household type	2A1mCu18 vs. 2Ay1830	124	53	2.15	1.58	0.33	3.7e-03**	[0.19, 0.47]	medium
16	household type	2A1mCu14 vs. SP	266	10	1.99	1.10	0.13	3.8e-03**	[0.51, 0.86]	large
17	household type	2A1mCu14 vs. 3mA	266	350	1.99	2.53	0.67	3.9e-03**	[-0.42, -0.26]	medium
18	household type	2A1mCu14 vs. 2Ay60p	266	383	1.99	1.57	0.34	4.0e-03**	[0.24, 0.39]	medium
19	household type	2A1mCu14 vs. 2Ay3060	266	707	1.99	1.77	0.42	4.1e-03**	[0.09, 0.23]	small
20	household type	1A60p vs. 3mA	128	350	0.91	2.53	0.92	4.2e-03**	[-0.88, -0.79]	large
21	household type	1A60p vs. 2Ay60p	128	383	0.91	1.57	0.76	4.3e-03**	[-0.59, -0.45]	large
22	household type	1A60p vs. 2Ay3060	128	707	0.91	1.77	0.83	4.4e-03**	[-0.72, -0.60]	large
23	household type	2A1mCu18 vs. 2A1mCu6	124	202	2.15	1.82	0.39	4.4e-03**	[0.11, 0.32]	small
24	household type	1A60p vs. 2Ay1830	128	53	0.91	1.58	0.77	4.5e-03**	[-0.69, -0.38]	large
25	household type	1A60p vs. 2A1mCu6	128	202	0.91	1.82	0.84	4.6e-03**	[-0.75, -0.60]	large
26	household type	1A60p vs. 2A1mCu18	128	124	0.91	2.15	0.90	4.7e-03**	[-0.86, -0.72]	large
27	household type	1A60p vs. 2A1mCu14	128	266	0.91	1.99	0.89	4.8e-03**	[-0.84, -0.72]	large
28	household type	1A3060 vs. 3mA	167	350	1.10	2.53	0.88	4.9e-03**	[-0.82, -0.70]	large
29	household type	1A3060 vs. 2Ay60p	167	383	1.10	1.57	0.69	5.0e-03**	[-0.47, -0.30]	medium
30	household type	1A3060 vs. 2Ay3060	167	707	1.10	1.77	0.77	5.1e-03**	[-0.60, -0.46]	large
31	household type	1A3060 vs. 2Ay1830	167	53	1.10	1.58	0.71	5.2e-03**	[-0.57, -0.25]	medium
32	household type	1A3060 vs. 2A1mCu6	167	202	1.10	1.82	0.78	5.3e-03**	[-0.64, -0.46]	large
33	household type	1A3060 vs. 2A1mCu18	167	124	1.10	2.15	0.85	5.4e-03**	[-0.77, -0.60]	large
34	household type	1A3060 vs. 2A1mCu14	167	266	1.10	1.99	0.83	5.5e-03**	[-0.74, -0.58]	large
35	household type	2A1mCu14 vs. 2Ay1830	266	53	1.99	1.58	0.37	8.4e-03**	[0.12, 0.40]	small
36	household type	2Ay1830 vs. SP	53	10	1.58	1.10	0.27	2.0e-02*	[0.19, 0.66]	medium
37	household type	2A1mCu14 vs. 2A1mCu6	266	202	1.99	1.82	0.43	5.7e-02	n/c	n/c
38	household type	1A3060 vs. 1A60p	167	128	1.10	0.91	0.43	9.0e-02	n/c	n/c
39	household type	1A1830 vs. 3mA	11	350	1.55	2.53	0.78	3.2e-01	n/c	n/c
40	household type	1A60p vs. SP	128	10	0.91	1.10	0.59	7.2e-01	n/c	n/c
41	household type	1A1830 vs. 2A1mCu18	11	124	1.55	2.15	0.75	7.5e-01	n/c	n/c
42	household type	1A1830 vs. 2A1mCu14	11	266	1.55	1.99	0.74	9.1e-01	n/c	n/c
43	household type	1A1830 vs. 1A3060	11	167	1.55	1.10	0.51	9.3e-01	n/c	n/c
44	household type	1A1830 vs. 2Ay3060	11	707	1.55	1.77	0.69	1.2e+00	n/c	n/c
45	household type	2A1mCu14 vs. 2A1mCu18	266	124	1.99	2.15	0.55	1.2e+00	n/c	n/c
46	household type	2A1mCu6 vs. 2Ay1830	202	53	1.82	1.58	0.43	1.2e+00	n/c	n/c
47	household type	2Ay1830 vs. 2Ay3060	53	707	1.58	1.77	0.55	1.3e+00	n/c	n/c
48	household type	1A1830 vs. 2A1mCu6	11	202	1.55	1.82	0.70	1.3e+00	n/c	n/c
49	household type	1A1830 vs. 2Ay60p	11	383	1.55	1.57	0.64	1.5e+00	n/c	n/c
50	household type	1A1830 vs. SP	11	10	1.55	1.10	0.53	1.6e+00	n/c	n/c
51	household type	1A1830 vs. 2Ay1830	11	53	1.55	1.58	0.65	1.8e+00	n/c	n/c
52	household type	1A3060 vs. SP	167	10	1.10	1.10	0.51	2.4e+00	n/c	n/c
53	household type	1A1830 vs. 1A60p	11	128	1.55	0.91	0.46	2.8e+00	n/c	n/c
54	household type	2A1mCu6 vs. 2Ay3060	202	707	1.82	1.77	0.49	2.9e+00	n/c	n/c
55	household type	2Ay1830 vs. 2Ay60p	53	383	1.58	1.57	0.48	3.2e+00	n/c	n/c
56	place of residence	city vs. urban	878	1116	1.58	1.93	0.62	2e-04***	[-0.28, -0.19]	small
57	place of residence	city vs. rural	878	416	1.58	1.91	0.61	3e-04***	[-0.27, -0.15]	small
58	place of residence	rural vs. urban	416	1116	1.91	1.93	0.51	6e-01	n/c	n/c

Significance codes: $0.0 < \text{p***} \leq 0.001 < \text{p**} \leq 0.01 < \text{p*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

A.4.2 Vehicle level

Table 38: Vehicle level (Cliff's Method): main effects on number of trips per (use) day (I)

	Factor	Level$_1$ vs. level$_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	low vs. medium	1993	8777	3.75	3.46	0.46	1.0e-03***	[0.04, 0.10]	negligible
2	economic status	low vs. verylow	1993	1361	3.75	3.44	0.46	1.8e-03**	[0.04, 0.11]	negligible
3	economic status	high vs. medium	7315	8777	3.57	3.46	0.49	7.2e-03**	[0.01, 0.05]	negligible
4	economic status	low vs. veryhigh	1993	2606	3.75	3.49	0.47	1.4e-02*	[0.02, 0.09]	negligible
5	economic status	high vs. low	7315	1993	3.57	3.75	0.52	2.4e-02*	[-0.07, -0.01]	negligible
6	economic status	high vs. verylow	7315	1361	3.57	3.44	0.48	1.7e-01	n/c	n/c
7	economic status	medium vs. veryhigh	8777	2606	3.46	3.49	0.51	5.6e-01	n/c	n/c
8	economic status	veryhigh vs. verylow	2606	1361	3.49	3.44	0.49	6.0e-01	n/c	n/c
9	economic status	medium vs. verylow	8777	1361	3.46	3.44	0.50	7.2e-01	n/c	n/c
10	economic status	high vs. veryhigh	7315	2606	3.57	3.49	0.49	7.6e-01	n/c	n/c
11	household type	2Ay3060 vs. SP	3872	292	3.23	3.72	0.58	3.0e-03**	[-0.23, -0.09]	small
12	household type	2Ay3060 vs. 3mA	3872	4475	3.23	3.45	0.52	3.1e-03**	[-0.07, -0.03]	negligible
13	household type	2Ay1830 vs. SP	567	292	3.08	3.72	0.60	3.2e-03**	[-0.28, -0.12]	small
14	household type	2Ay1830 vs. 3mA	567	4475	3.08	3.45	0.55	3.3e-03**	[-0.14, -0.05]	negligible
15	household type	2A1mCu6 vs. 3mA	2116	4475	3.90	3.45	0.45	3.4e-03**	[0.08, 0.14]	small
16	household type	2A1mCu6 vs. 2Ay60p	2116	3524	3.90	3.35	0.44	3.5e-03**	[0.10, 0.16]	small
17	household type	2A1mCu6 vs. 2Ay3060	2116	3872	3.90	3.23	0.42	3.6e-03**	[0.13, 0.19]	small
18	household type	2A1mCu6 vs. 2Ay1830	2116	567	3.90	3.08	0.40	3.7e-03**	[0.15, 0.25]	small
19	household type	2A1mCu18 vs. 3mA	2266	4475	3.81	3.45	0.45	3.8e-03**	[0.07, 0.12]	negligible
20	household type	2A1mCu18 vs. 2Ay60p	2266	3524	3.81	3.35	0.44	3.9e-03**	[0.09, 0.15]	small
21	household type	2A1mCu18 vs. 2Ay3060	2266	3872	3.81	3.23	0.43	4.0e-03**	[0.12, 0.18]	small
22	household type	2A1mCu18 vs. 2Ay1830	2266	567	3.81	3.08	0.41	4.1e-03**	[0.14, 0.24]	small
23	household type	2A1mCu14 vs. 3mA	3382	4475	4.00	3.45	0.43	4.2e-03**	[0.11, 0.16]	small
24	household type	2A1mCu14 vs. 2Ay60p	3382	3524	4.00	3.35	0.42	4.3e-03**	[0.13, 0.18]	small
25	household type	2A1mCu14 vs. 2Ay3060	3382	3872	4.00	3.23	0.41	4.4e-03**	[0.16, 0.21]	small
26	household type	2A1mCu14 vs. 2Ay1830	3382	567	4.00	3.08	0.39	4.5e-03**	[0.18, 0.27]	small
27	household type	1A60p vs. SP	613	292	3.15	3.72	0.59	4.6e-03**	[-0.25, -0.10]	small
28	household type	1A60p vs. 2A1mCu6	613	2116	3.15	3.90	0.59	4.7e-03**	[-0.22, -0.12]	small
29	household type	1A60p vs. 2A1mCu18	613	2266	3.15	3.81	0.58	4.8e-03**	[-0.21, -0.11]	small
30	household type	1A60p vs. 2A1mCu14	613	3382	3.15	4.00	0.60	4.9e-03**	[-0.25, -0.16]	small
31	household type	1A3060 vs. SP	772	292	3.08	3.72	0.60	5.0e-03**	[-0.27, -0.12]	small
32	household type	1A3060 vs. 3mA	772	4475	3.08	3.45	0.54	5.1e-03**	[-0.12, -0.04]	negligible
33	household type	1A3060 vs. 2A1mCu6	772	2116	3.08	3.90	0.60	5.2e-03**	[-0.24, -0.15]	small
34	household type	1A3060 vs. 2A1mCu18	772	2266	3.08	3.81	0.59	5.3e-03**	[-0.22, -0.14]	small
35	household type	1A3060 vs. 2A1mCu14	772	3382	3.08	4.00	0.61	5.4e-03**	[-0.26, -0.18]	small
36	household type	1A1830 vs. 2A1mCu14	109	3382	3.08	4.00	0.61	5.5e-03**	[-0.31, -0.12]	small
37	household type	2Ay60p vs. SP	3524	292	3.35	3.72	0.56	5.6e-03**	[-0.19, -0.06]	small
38	household type	1A1830 vs. 2A1mCu6	109	2116	3.08	3.90	0.59	5.8e-03**	[-0.29, -0.09]	small
39	household type	1A1830 vs. 2A1mCu18	109	2266	3.08	3.81	0.59	1.3e-02*	[-0.27, -0.08]	small
40	household type	3mA vs. SP	4475	292	3.45	3.72	0.55	5.0e-02*	[-0.17, -0.04]	small
41	household type	1A1830 vs. SP	109	292	3.08	3.72	0.60	5.2e-02	n/c	n/c
42	household type	2Ay1830 vs. 2Ay60p	567	3524	3.08	3.35	0.54	9.2e-02	n/c	n/c
43	household type	1A3060 vs. 2Ay60p	772	3524	3.08	3.35	0.53	9.6e-02	n/c	n/c
44	household type	2A1mCu14 vs. 2A1mCu18	3382	2266	4.00	3.81	0.48	1.5e-01	n/c	n/c
45	household type	1A60p vs. 3mA	613	4475	3.15	3.45	0.53	1.5e-01	n/c	n/c
46	household type	2Ay3060 vs. 2Ay60p	3872	3524	3.23	3.35	0.51	6.4e-01	n/c	n/c
47	household type	1A1830 vs. 1A3060	109	772	3.08	3.08	0.50	9.6e-01	n/c	n/c
48	household type	2A1mCu14 vs. 2A1mCu6	3382	2116	4.00	3.90	0.49	1.3e+00	n/c	n/c
49	household type	2Ay1830 vs. 2Ay3060	567	3872	3.08	3.23	0.52	1.3e+00	n/c	n/c
50	household type	2Ay60p vs. 3mA	3524	4475	3.35	3.45	0.51	1.4e+00	n/c	n/c
51	household type	1A60p vs. 2Ay60p	613	3524	3.15	3.35	0.52	1.4e+00	n/c	n/c
52	household type	1A1830 vs. 3mA	109	4475	3.08	3.45	0.54	1.6e+00	n/c	n/c
53	household type	1A3060 vs. 2Ay3060	772	3872	3.08	3.23	0.52	1.7e+00	n/c	n/c
54	household type	1A1830 vs. 2Ay1830	109	567	3.08	3.08	0.50	1.8e+00	n/c	n/c
55	household type	2A1mCu18 vs. SP	2266	292	3.81	3.72	0.50	2.6e+00	n/c	n/c
56	household type	2A1mCu14 vs. SP	3382	292	4.00	3.72	0.48	3.1e+00	n/c	n/c
57	household type	1A1830 vs. 2Ay60p	109	3524	3.08	3.35	0.53	3.2e+00	n/c	n/c
58	household type	2A1mCu6 vs. SP	2116	292	3.90	3.72	0.50	3.3e+00	n/c	n/c
59	household type	1A60p vs. 2Ay1830	613	567	3.15	3.08	0.48	3.5e+00	n/c	n/c
60	household type	1A3060 vs. 2Ay1830	772	567	3.08	3.08	0.49	3.6e+00	n/c	n/c
61	household type	1A1830 vs. 1A60p	109	613	3.08	3.15	0.51	4.2e+00	n/c	n/c
62	household type	1A1830 vs. 2Ay3060	109	3872	3.08	3.23	0.52	4.2e+00	n/c	n/c
63	household type	1A60p vs. 2Ay3060	613	3872	3.15	3.23	0.51	4.3e+00	n/c	n/c
64	household type	1A3060 vs. 1A60p	772	613	3.08	3.15	0.51	4.3e+00	n/c	n/c
65	household type	2A1mCu18 vs. 2A1mCu6	2266	2116	3.81	3.90	0.51	4.7e+00	n/c	n/c
66	household type, combined	1-3A vs. 2A1mCu6-18+SP	13932	8056	3.31	3.91	0.57	1e-04***	[-0.16, -0.13]	small

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 39: Vehicle level (Cliff's Method): main effects on number of trips per (use) day (II)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
67	occupation	pensioner vs. unemployed	4384	554	3.35	3.75	0.55	1.2e-03**	[-0.16, -0.06]	small
68	occupation	homemaker vs. student	1488	418	4.08	3.48	0.43	1.3e-03**	[0.08, 0.20]	small
69	occupation	homemaker vs. pensioner	1488	4384	4.08	3.35	0.41	1.4e-03**	[0.14, 0.21]	small
70	occupation	halftime vs. student	3830	418	4.03	3.48	0.42	1.5e-03**	[0.09, 0.21]	small
71	occupation	halftime vs. pensioner	3830	4384	4.03	3.35	0.41	1.6e-03**	[0.16, 0.21]	small
72	occupation	fulltime vs. unemployed	10129	554	3.28	3.75	0.57	1.7e-03**	[-0.18, -0.08]	small
73	occupation	fulltime vs. homemaker	10129	1488	3.28	4.08	0.60	1.8e-03**	[-0.23, -0.17]	small
74	occupation	fulltime vs. halftime	10129	3830	3.28	4.03	0.61	1.9e-03**	[-0.23, -0.19]	small
75	occupation	apprentice vs. homemaker	559	1488	3.46	4.08	0.58	2.0e-03**	[-0.21, -0.11]	small
76	occupation	apprentice vs. halftime	559	3830	3.46	4.03	0.59	2.1e-03**	[-0.22, -0.12]	small
77	occupation	halftime vs. unemployed	3830	554	4.03	3.75	0.46	2.2e-02*	[0.03, 0.13]	negligible
78	occupation	apprentice vs. unemployed	559	554	3.46	3.75	0.55	7.0e-02	n/c	n/c
79	occupation	homemaker vs. unemployed	1488	554	4.08	3.75	0.46	7.2e-02	n/c	n/c
80	occupation	fulltime vs. pensioner	10129	4384	3.28	3.35	0.51	1.8e-01	n/c	n/c
81	occupation	student vs. unemployed	418	554	3.48	3.75	0.54	3.2e-01	n/c	n/c
82	occupation	fulltime vs. student	10129	418	3.28	3.48	0.53	4.1e-01	n/c	n/c
83	occupation	apprentice vs. fulltime	559	10129	3.46	3.28	0.48	6.5e-01	n/c	n/c
84	occupation	halftime vs. homemaker	3830	1488	4.03	4.08	0.50	8.2e-01	n/c	n/c
85	occupation	pensioner vs. student	4384	418	3.35	3.48	0.52	1.2e+00	n/c	n/c
86	occupation	apprentice vs. student	559	418	3.46	3.48	0.51	1.4e+00	n/c	n/c
87	occupation	apprentice vs. pensioner	559	4384	3.46	3.35	0.49	1.7e+00	n/c	n/c
88	place of residence	city vs. urban	5222	11135	3.39	3.61	0.52	3.0e-04***	[-0.07, -0.03]	negligible
89	place of residence	rural vs. urban	5695	11135	3.50	3.61	0.51	1.3e-02*	[-0.04, -0.01]	negligible
90	place of residence	city vs. rural	5222	5695	3.39	3.50	0.51	2.6e-02*	[-0.05, -0.01]	negligible
91	season	spring vs. summer	4863	4604	3.63	3.43	0.47	6.0e-04***	[0.03, 0.07]	negligible
92	season	fall vs. spring	6024	4863	3.52	3.63	0.51	3.6e-02*	[-0.05, 0.00]	negligible
93	season	spring vs. winter	4863	6561	3.63	3.52	0.49	5.1e-02	n/c	n/c
94	season	summer vs. winter	4604	6561	3.43	3.52	0.51	5.5e-02	n/c	n/c
95	season	fall vs. summer	6024	4604	3.52	3.43	0.49	5.6e-02	n/c	n/c
96	season	fall vs. winter	6024	6561	3.52	3.52	0.50	9.9e-01	n/c	n/c
97	vehicle use freq.	daily vs. weekly	13873	3448	3.78	3.27	0.43	2.0e-04***	[0.12, 0.16]	small
98	vehicle use freq.	daily vs. rarely	13873	165	3.78	2.90	0.38	3.0e-04***	[0.16, 0.31]	small
99	vehicle use freq.	rarely vs. weekly	165	3448	2.90	3.27	0.55	1.9e-02*	[-0.18, -0.02]	small
100	weekday	sunday vs. workday	2141	17030	2.70	3.63	0.64	2e-04***	[-0.30, -0.25]	small
101	weekday	saturday vs. sunday	2881	2141	3.52	2.70	0.38	3e-04***	[0.20, 0.26]	small
102	weekday	saturday vs. workday	2881	17030	3.52	3.63	0.52	2e-03**	[-0.06, -0.01]	negligible

Significance codes: $0.0 <$ p*** $\leq 0.001 <$ p** $\leq 0.01 <$ p* ≤ 0.05
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 40: Vehicle level (Cliff's Method): interaction effects on number of trips per (use) day controlling for combined household type = 1-3A (I)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	high vs. medium	4616	5792	3.36	3.26	0.49	9.0e-02	n/c	n/c
2	economic status	veryhigh vs. verylow	1798	924	3.26	3.33	0.50	9.9e-01	n/c	n/c
3	economic status	low vs. verylow	802	924	3.42	3.33	0.49	1.8e+00	n/c	n/c
4	economic status	high vs. low	4616	802	3.36	3.42	0.50	1.8e+00	n/c	n/c
5	economic status	low vs. medium	802	5792	3.42	3.26	0.49	2.1e+00	n/c	n/c
6	economic status	high vs. veryhigh	4616	1798	3.36	3.26	0.49	2.1e+00	n/c	n/c
7	economic status	medium vs. verylow	5792	924	3.26	3.33	0.51	2.3e+00	n/c	n/c
8	economic status	medium vs. veryhigh	5792	1798	3.26	3.26	0.51	2.6e+00	n/c	n/c
9	economic status	low vs. veryhigh	802	1798	3.42	3.26	0.49	2.8e+00	n/c	n/c
10	economic status	high vs. verylow	4616	924	3.36	3.33	0.49	2.9e+00	n/c	n/c
11	household type	1A1830 vs. 2A1mCu14	109	0	3.08	n/a	n/a	n/a	n/a	n/a
12	household type	1A1830 vs. 2A1mCu18	109	0	3.08	n/a	n/a	n/a	n/a	n/a
13	household type	1A1830 vs. 2A1mCu6	109	0	3.08	n/a	n/a	n/a	n/a	n/a
14	household type	1A1830 vs. SP	109	0	3.08	n/a	n/a	n/a	n/a	n/a
15	household type	1A3060 vs. 2A1mCu14	772	0	3.08	n/a	n/a	n/a	n/a	n/a
16	household type	1A3060 vs. 2A1mCu18	772	0	3.08	n/a	n/a	n/a	n/a	n/a
17	household type	1A3060 vs. 2A1mCu6	772	0	3.08	n/a	n/a	n/a	n/a	n/a
18	household type	1A3060 vs. SP	772	0	3.08	n/a	n/a	n/a	n/a	n/a
19	household type	1A60p vs. 2A1mCu14	613	0	3.15	n/a	n/a	n/a	n/a	n/a
20	household type	1A60p vs. 2A1mCu18	613	0	3.15	n/a	n/a	n/a	n/a	n/a
21	household type	1A60p vs. 2A1mCu6	613	0	3.15	n/a	n/a	n/a	n/a	n/a
22	household type	1A60p vs. SP	613	0	3.15	n/a	n/a	n/a	n/a	n/a
23	household type	2A1mCu14 vs. 2A1mCu18	0	0	n/a	n/a	n/a	n/a	n/a	n/a
24	household type	2A1mCu14 vs. 2A1mCu6	0	0	n/a	n/a	n/a	n/a	n/a	n/a
25	household type	2A1mCu14 vs. 2Ay1830	0	567	n/a	3.08	n/a	n/a	n/a	n/a
26	household type	2A1mCu14 vs. 2Ay3060	0	3872	n/a	3.23	n/a	n/a	n/a	n/a
27	household type	2A1mCu14 vs. 2Ay60p	0	3524	n/a	3.35	n/a	n/a	n/a	n/a
28	household type	2A1mCu14 vs. 3mA	0	4475	n/a	3.45	n/a	n/a	n/a	n/a
29	household type	2A1mCu14 vs. SP	0	0	n/a	n/a	n/a	n/a	n/a	n/a
30	household type	2A1mCu18 vs. 2A1mCu6	0	0	n/a	n/a	n/a	n/a	n/a	n/a
31	household type	2A1mCu18 vs. 2Ay1830	0	567	n/a	3.08	n/a	n/a	n/a	n/a
32	household type	2A1mCu18 vs. 2Ay3060	0	3872	n/a	3.23	n/a	n/a	n/a	n/a
33	household type	2A1mCu18 vs. 2Ay60p	0	3524	n/a	3.35	n/a	n/a	n/a	n/a
34	household type	2A1mCu18 vs. 3mA	0	4475	n/a	3.45	n/a	n/a	n/a	n/a
35	household type	2A1mCu18 vs. SP	0	0	n/a	n/a	n/a	n/a	n/a	n/a
36	household type	2A1mCu6 vs. 2Ay1830	0	567	n/a	3.08	n/a	n/a	n/a	n/a
37	household type	2A1mCu6 vs. 2Ay3060	0	3872	n/a	3.23	n/a	n/a	n/a	n/a
38	household type	2A1mCu6 vs. 2Ay60p	0	3524	n/a	3.35	n/a	n/a	n/a	n/a
39	household type	2A1mCu6 vs. 3mA	0	4475	n/a	3.45	n/a	n/a	n/a	n/a
40	household type	2A1mCu6 vs. SP	0	0	n/a	n/a	n/a	n/a	n/a	n/a
41	household type	2Ay1830 vs. SP	567	0	3.08	n/a	n/a	n/a	n/a	n/a
42	household type	2Ay3060 vs. SP	3872	0	3.23	n/a	n/a	n/a	n/a	n/a
43	household type	2Ay60p vs. SP	3524	0	3.35	n/a	n/a	n/a	n/a	n/a
44	household type	3mA vs. SP	4475	0	3.45	n/a	n/a	n/a	n/a	n/a
45	household type	2Ay3060 vs. 3mA	3872	4475	3.23	3.45	0.52	5.3e-03**	[-0.07, -0.03]	negligible
46	household type	2Ay1830 vs. 3mA	567	4475	3.08	3.45	0.55	5.4e-03**	[-0.14, -0.05]	negligible
47	household type	1A3060 vs. 3mA	772	4475	3.08	3.45	0.54	5.5e-03**	[-0.12, -0.04]	negligible
48	household type	2Ay1830 vs. 2Ay60p	567	3524	3.08	3.35	0.54	2.0e-01	n/c	n/c
49	household type	1A3060 vs. 2Ay60p	772	3524	3.08	3.35	0.53	2.1e-01	n/c	n/c
50	household type	1A60p vs. 3mA	613	4475	3.15	3.45	0.53	3.5e-01	n/c	n/c
51	household type	2Ay3060 vs. 2Ay60p	3872	3524	3.23	3.35	0.51	1.6e+00	n/c	n/c
52	household type	2Ay1830 vs. 2Ay3060	567	3872	3.08	3.23	0.52	3.5e+00	n/c	n/c
53	household type	2Ay60p vs. 3mA	3524	4475	3.35	3.45	0.51	3.9e+00	n/c	n/c
54	household type	1A60p vs. 2Ay60p	613	3524	3.15	3.35	0.52	4.0e+00	n/c	n/c
55	household type	1A1830 vs. 3mA	109	4475	3.08	3.45	0.54	5.0e+00	n/c	n/c
56	household type	1A3060 vs. 2Ay3060	772	3872	3.08	3.23	0.52	5.3e+00	n/c	n/c
57	household type	1A1830 vs. 2Ay60p	109	3524	3.08	3.35	0.53	1.1e+01	n/c	n/c
58	household type	1A60p vs. 2Ay1830	613	567	3.15	3.08	0.48	1.3e+01	n/c	n/c
59	household type	1A3060 vs. 1A60p	772	613	3.08	3.15	0.51	2.0e+01	n/c	n/c
60	household type	1A1830 vs. 2Ay3060	109	3872	3.08	3.23	0.52	2.1e+01	n/c	n/c
61	household type	1A60p vs. 2Ay3060	613	3872	3.15	3.23	0.51	2.4e+01	n/c	n/c
62	household type	1A1830 vs. 1A60p	109	613	3.08	3.15	0.51	2.7e+01	n/c	n/c
63	household type	1A3060 vs. 2Ay1830	772	567	3.08	3.08	0.49	2.7e+01	n/c	n/c
64	household type	1A1830 vs. 2Ay1830	109	567	3.08	3.08	0.50	3.2e+01	n/c	n/c
65	household type	1A1830 vs. 1A3060	109	772	3.08	3.08	0.50	3.4e+01	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 41: Vehicle level (Cliff's Method): interaction effects on number of trips per (use) day controlling for combined household type = 1-3A (II)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
66	occupation	homemaker vs. pensioner	778	4252	3.78	3.34	0.44	1.6e-03**	[0.08, 0.17]	small
67	occupation	halftime vs. pensioner	1636	4252	3.63	3.34	0.45	1.7e-03**	[0.07, 0.13]	negligible
68	occupation	fulltime vs. pensioner	5911	4252	3.09	3.34	0.53	1.8e-03**	[-0.09, -0.05]	negligible
69	occupation	fulltime vs. homemaker	5911	778	3.09	3.78	0.60	1.9e-03**	[-0.24, -0.15]	small
70	occupation	fulltime vs. halftime	5911	1636	3.09	3.63	0.59	2.0e-03**	[-0.20, -0.14]	small
71	occupation	apprentice vs. homemaker	359	778	3.32	3.78	0.57	2.1e-03**	[-0.21, -0.07]	small
72	occupation	apprentice vs. halftime	359	1636	3.32	3.63	0.55	1.4e-02*	[-0.17, -0.05]	small
73	occupation	homemaker vs. student	778	332	3.78	3.36	0.44	2.6e-02*	[0.05, 0.19]	small
74	occupation	fulltime vs. unemployed	5911	269	3.09	3.46	0.56	2.8e-02*	[-0.18, -0.05]	small
75	occupation	halftime vs. student	1636	332	3.63	3.36	0.46	1.4e-01	n/c	n/c
76	occupation	homemaker vs. unemployed	778	269	3.78	3.46	0.45	1.8e-01	n/c	n/c
77	occupation	fulltime vs. student	5911	332	3.09	3.36	0.54	2.9e-01	n/c	n/c
78	occupation	apprentice vs. fulltime	359	5911	3.32	3.09	0.47	4.6e-01	n/c	n/c
79	occupation	halftime vs. unemployed	1636	269	3.63	3.46	0.47	8.8e-01	n/c	n/c
80	occupation	pensioner vs. student	4252	332	3.34	3.36	0.50	8.8e-01	n/c	n/c
81	occupation	halftime vs. homemaker	1636	778	3.63	3.78	0.52	1.2e+00	n/c	n/c
82	occupation	pensioner vs. unemployed	4252	269	3.34	3.46	0.52	1.3e+00	n/c	n/c
83	occupation	apprentice vs. student	359	332	3.32	3.36	0.51	1.4e+00	n/c	n/c
84	occupation	apprentice vs. unemployed	359	269	3.32	3.46	0.53	1.6e+00	n/c	n/c
85	occupation	student vs. unemployed	332	269	3.36	3.46	0.52	2.0e+00	n/c	n/c
86	occupation	apprentice vs. pensioner	359	4252	3.32	3.34	0.51	2.2e+00	n/c	n/c
87	place of residence	city vs. urban	3626	6770	3.23	3.35	0.51	3.0e-02*	[-0.05, -0.01]	negligible
88	place of residence	city vs. rural	3626	3536	3.23	3.31	0.51	2.6e-01	n/c	n/c
89	place of residence	rural vs. urban	3536	6770	3.31	3.35	0.50	4.3e-01	n/c	n/c
90	season	spring vs. summer	2955	3025	3.38	3.29	0.48	9.0e-02	n/c	n/c
91	season	spring vs. winter	2955	4183	3.38	3.28	0.49	2.5e-01	n/c	n/c
92	season	fall vs. spring	3769	2955	3.30	3.38	0.51	4.8e-01	n/c	n/c
93	season	fall vs. winter	3769	4183	3.30	3.28	0.50	7.3e-01	n/c	n/c
94	season	fall vs. summer	3769	3025	3.30	3.29	0.49	9.3e-01	n/c	n/c
95	season	summer vs. winter	3025	4183	3.29	3.28	0.50	9.6e-01	n/c	n/c
96	vehicle use freq.	daily vs. weekly	8411	2534	3.53	3.10	0.44	2.0e-04***	[0.10, 0.15]	small
97	vehicle use freq.	daily vs. rarely	8411	132	3.53	2.83	0.40	3.0e-04***	[0.11, 0.28]	small
98	vehicle use freq.	rarely vs. weekly	132	2534	2.83	3.10	0.53	1.5e-01	n/c	n/c
99	weekday	sunday vs. workday	1317	10809	2.62	3.39	0.62	2e-04***	[-0.28, -0.22]	small
100	weekday	saturday vs. sunday	1806	1317	3.32	2.62	0.40	3e-04***	[0.17, 0.24]	small
101	weekday	saturday vs. workday	1806	10809	3.32	3.39	0.52	9e-03**	[-0.07, -0.01]	negligible

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 42: Vehicle level (Cliff's Method): interaction effects on number of trips per (use) day controlling for combined household type = 2A1mCu6-18+SP (I)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	veryhigh vs. verylow	801	437	4.01	3.68	0.45	7.0e-02	n/c	n/c
2	economic status	medium vs. veryhigh	2952	801	3.86	4.01	0.53	1.7e-01	n/c	n/c
3	economic status	low vs. verylow	1186	437	3.97	3.68	0.46	1.7e-01	n/c	n/c
4	economic status	high vs. verylow	2680	437	3.94	3.68	0.47	2.7e-01	n/c	n/c
5	economic status	low vs. medium	1186	2952	3.97	3.86	0.48	3.5e-01	n/c	n/c
6	economic status	low vs. veryhigh	1186	801	3.97	4.01	0.51	5.3e-01	n/c	n/c
7	economic status	medium vs. verylow	2952	437	3.86	3.68	0.48	6.0e-01	n/c	n/c
8	economic status	high vs. medium	2680	2952	3.94	3.86	0.49	7.5e-01	n/c	n/c
9	economic status	high vs. veryhigh	2680	801	3.94	4.01	0.51	8.0e-01	n/c	n/c
10	economic status	high vs. low	2680	1186	3.94	3.97	0.51	9.8e-01	n/c	n/c
11	household type	1A1830 vs. 1A3060	0	0	n/a	n/a	n/a	n/a	n/a	n/a
12	household type	1A1830 vs. 1A60p	0	0	n/a	n/a	n/a	n/a	n/a	n/a
13	household type	1A1830 vs. 2A1mCu14	0	3382	n/a	4.00	n/a	n/a	n/a	n/a
14	household type	1A1830 vs. 2A1mCu18	0	2266	n/a	3.81	n/a	n/a	n/a	n/a
15	household type	1A1830 vs. 2A1mCu6	0	2116	n/a	3.90	n/a	n/a	n/a	n/a
16	household type	1A1830 vs. 2Ay1830	0	0	n/a	n/a	n/a	n/a	n/a	n/a
17	household type	1A1830 vs. 2Ay3060	0	0	n/a	n/a	n/a	n/a	n/a	n/a
18	household type	1A1830 vs. 2Ay60p	0	0	n/a	n/a	n/a	n/a	n/a	n/a
19	household type	1A1830 vs. 3mA	0	0	n/a	n/a	n/a	n/a	n/a	n/a
20	household type	1A1830 vs. SP	0	292	n/a	3.72	n/a	n/a	n/a	n/a
21	household type	1A3060 vs. 1A60p	0	0	n/a	n/a	n/a	n/a	n/a	n/a
22	household type	1A3060 vs. 2A1mCu14	0	3382	n/a	4.00	n/a	n/a	n/a	n/a
23	household type	1A3060 vs. 2A1mCu18	0	2266	n/a	3.81	n/a	n/a	n/a	n/a
24	household type	1A3060 vs. 2A1mCu6	0	2116	n/a	3.90	n/a	n/a	n/a	n/a
25	household type	1A3060 vs. 2Ay1830	0	0	n/a	n/a	n/a	n/a	n/a	n/a
26	household type	1A3060 vs. 2Ay3060	0	0	n/a	n/a	n/a	n/a	n/a	n/a
27	household type	1A3060 vs. 2Ay60p	0	0	n/a	n/a	n/a	n/a	n/a	n/a
28	household type	1A3060 vs. 3mA	0	0	n/a	n/a	n/a	n/a	n/a	n/a
29	household type	1A3060 vs. SP	0	292	n/a	3.72	n/a	n/a	n/a	n/a
30	household type	1A60p vs. 2A1mCu14	0	3382	n/a	4.00	n/a	n/a	n/a	n/a
31	household type	1A60p vs. 2A1mCu18	0	2266	n/a	3.81	n/a	n/a	n/a	n/a
32	household type	1A60p vs. 2A1mCu6	0	2116	n/a	3.90	n/a	n/a	n/a	n/a
33	household type	1A60p vs. 2Ay1830	0	0	n/a	n/a	n/a	n/a	n/a	n/a
34	household type	1A60p vs. 2Ay3060	0	0	n/a	n/a	n/a	n/a	n/a	n/a
35	household type	1A60p vs. 2Ay60p	0	0	n/a	n/a	n/a	n/a	n/a	n/a
36	household type	1A60p vs. 3mA	0	0	n/a	n/a	n/a	n/a	n/a	n/a
37	household type	1A60p vs. SP	0	292	n/a	3.72	n/a	n/a	n/a	n/a
38	household type	2A1mCu14 vs. 2Ay1830	3382	0	4.00	n/a	n/a	n/a	n/a	n/a
39	household type	2A1mCu14 vs. 2Ay3060	3382	0	4.00	n/a	n/a	n/a	n/a	n/a
40	household type	2A1mCu14 vs. 2Ay60p	3382	0	4.00	n/a	n/a	n/a	n/a	n/a
41	household type	2A1mCu14 vs. 3mA	3382	0	4.00	n/a	n/a	n/a	n/a	n/a
42	household type	2A1mCu18 vs. 2Ay1830	2266	0	3.81	n/a	n/a	n/a	n/a	n/a
43	household type	2A1mCu18 vs. 2Ay3060	2266	0	3.81	n/a	n/a	n/a	n/a	n/a
44	household type	2A1mCu18 vs. 2Ay60p	2266	0	3.81	n/a	n/a	n/a	n/a	n/a
45	household type	2A1mCu18 vs. 3mA	2266	0	3.81	n/a	n/a	n/a	n/a	n/a
46	household type	2A1mCu6 vs. 2Ay1830	2116	0	3.90	n/a	n/a	n/a	n/a	n/a
47	household type	2A1mCu6 vs. 2Ay3060	2116	0	3.90	n/a	n/a	n/a	n/a	n/a
48	household type	2A1mCu6 vs. 2Ay60p	2116	0	3.90	n/a	n/a	n/a	n/a	n/a
49	household type	2A1mCu6 vs. 3mA	2116	0	3.90	n/a	n/a	n/a	n/a	n/a
50	household type	2Ay1830 vs. 2Ay3060	0	0	n/a	n/a	n/a	n/a	n/a	n/a
51	household type	2Ay1830 vs. 2Ay60p	0	0	n/a	n/a	n/a	n/a	n/a	n/a
52	household type	2Ay1830 vs. 3mA	0	0	n/a	n/a	n/a	n/a	n/a	n/a
53	household type	2Ay1830 vs. SP	0	292	n/a	3.72	n/a	n/a	n/a	n/a
54	household type	2Ay3060 vs. 2Ay60p	0	0	n/a	n/a	n/a	n/a	n/a	n/a
55	household type	2Ay3060 vs. 3mA	0	0	n/a	n/a	n/a	n/a	n/a	n/a
56	household type	2Ay3060 vs. SP	0	292	n/a	3.72	n/a	n/a	n/a	n/a
57	household type	2Ay60p vs. 3mA	0	0	n/a	n/a	n/a	n/a	n/a	n/a
58	household type	2Ay60p vs. SP	0	292	n/a	3.72	n/a	n/a	n/a	n/a
59	household type	3mA vs. SP	0	292	n/a	3.72	n/a	n/a	n/a	n/a
60	household type	2A1mCu14 vs. 2A1mCu18	3382	2266	4.00	3.81	0.48	3.9e-01	n/c	n/c
61	household type	2A1mCu14 vs. 2A1mCu6	3382	2116	4.00	3.90	0.49	3.6e+00	n/c	n/c
62	household type	2A1mCu14 vs. SP	3382	292	4.00	3.72	0.48	1.4e+01	n/c	n/c
63	household type	2A1mCu18 vs. 2A1mCu6	2266	2116	3.81	3.90	0.51	2.4e+01	n/c	n/c
64	household type	2A1mCu6 vs. SP	2116	292	3.90	3.72	0.50	4.2e+01	n/c	n/c
65	household type	2A1mCu18 vs. SP	2266	292	3.81	3.72	0.50	4.4e+01	n/c	n/c

Significance codes: $0.0 <$ p*** $\leq 0.001 <$ p** $\leq 0.01 <$ p* ≤ 0.05
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 43: Vehicle level (Cliff's Method): interaction effects on number of trips per (use) day controlling for combined household type = 2A1mCu6-18+SP (II)

	Factor	Level_1 vs. level_2	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
66	occupation	fulltime vs. homemaker	4182	707	3.55	4.40	0.60	2.0e-03**	[-0.24, -0.15]	small
67	occupation	fulltime vs. halftime	4182	2184	3.55	4.35	0.61	2.1e-03**	[-0.24, -0.18]	small
68	occupation	apprentice vs. halftime	197	2184	3.75	4.35	0.59	3.8e-03**	[-0.26, -0.08]	small
69	occupation	fulltime vs. unemployed	4182	285	3.55	4.03	0.57	5.4e-03**	[-0.20, -0.06]	small
70	occupation	apprentice vs. homemaker	197	707	3.75	4.40	0.58	1.2e-02*	[-0.24, -0.07]	small
71	occupation	halftime vs. pensioner	2184	122	4.35	3.95	0.44	2.9e-01	n/c	n/c
72	occupation	halftime vs. unemployed	2184	285	4.35	4.03	0.46	3.8e-01	n/c	n/c
73	occupation	homemaker vs. pensioner	707	122	4.40	3.95	0.44	5.9e-01	n/c	n/c
74	occupation	pensioner vs. student	122	85	3.95	3.94	0.51	8.6e-01	n/c	n/c
75	occupation	apprentice vs. unemployed	197	285	3.75	4.03	0.55	1.0e+00	n/c	n/c
76	occupation	homemaker vs. unemployed	707	285	4.40	4.03	0.47	1.0e+00	n/c	n/c
77	occupation	halftime vs. student	2184	85	4.35	3.94	0.45	1.1e+00	n/c	n/c
78	occupation	homemaker vs. student	707	85	4.40	3.94	0.45	1.2e+00	n/c	n/c
79	occupation	fulltime vs. pensioner	4182	122	3.55	3.95	0.54	1.3e+00	n/c	n/c
80	occupation	fulltime vs. student	4182	85	3.55	3.94	0.55	1.3e+00	n/c	n/c
81	occupation	student vs. unemployed	85	285	3.94	4.03	0.51	1.4e+00	n/c	n/c
82	occupation	halftime vs. homemaker	2184	707	4.35	4.40	0.49	2.0e+00	n/c	n/c
83	occupation	apprentice vs. fulltime	197	4182	3.75	3.55	0.49	2.1e+00	n/c	n/c
84	occupation	apprentice vs. pensioner	197	122	3.75	3.95	0.52	2.3e+00	n/c	n/c
85	occupation	pensioner vs. unemployed	122	285	3.95	4.03	0.52	2.8e+00	n/c	n/c
86	occupation	apprentice vs. student	197	85	3.75	3.94	0.53	2.8e+00	n/c	n/c
87	place of residence	rural vs. urban	2147	4335	3.82	4.01	0.52	1.0e-02**	[-0.07, -0.01]	negligible
88	place of residence	city vs. urban	1574	4335	3.76	4.01	0.52	1.2e-02*	[-0.08, -0.02]	negligible
89	place of residence	city vs. rural	1574	2147	3.76	3.82	0.50	7.6e-01	n/c	n/c
90	season	spring vs. summer	1889	1571	4.04	3.70	0.47	2.4e-03**	[0.03, 0.11]	negligible
91	season	summer vs. winter	1571	2365	3.70	3.97	0.53	1.5e-02*	[-0.09, -0.02]	negligible
92	season	fall vs. summer	2231	1571	3.89	3.70	0.48	1.4e-01	n/c	n/c
93	season	fall vs. spring	2231	1889	3.89	4.04	0.52	2.7e-01	n/c	n/c
94	season	spring vs. winter	1889	2365	4.04	3.97	0.49	4.1e-01	n/c	n/c
95	season	fall vs. winter	2231	2365	3.89	3.97	0.51	7.2e-01	n/c	n/c
96	vehicle use freq.	daily vs. weekly	5432	905	4.17	3.74	0.45	3.0e-04***	[0.06, 0.14]	negligible
97	vehicle use freq.	daily vs. rarely	5432	31	4.17	3.16	0.36	1.8e-02*	[0.07, 0.46]	small
98	vehicle use freq.	rarely vs. weekly	31	905	3.16	3.74	0.60	7.7e-02	n/c	n/c
99	weekday	sunday vs. workday	818	6171	2.82	4.06	0.66	2.0e-04***	[-0.36, -0.29]	medium
100	weekday	saturday vs. sunday	1067	818	3.87	2.82	0.36	3.0e-04***	[0.23, 0.33]	small
101	weekday	saturday vs. workday	1067	6171	3.87	4.06	0.52	2.9e-02*	[-0.08, 0.00]	negligible

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 44: Vehicle level (Cliff's Method): interaction effects on number of trips per (use) day controlling for weekday = workday (I)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	low vs. medium	1533	6812	3.88	3.58	0.46	1.0e-03***	[0.04, 0.10]	negligible
2	economic status	low vs. veryhigh	1533	1974	3.88	3.54	0.47	9.0e-03**	[0.03, 0.10]	negligible
3	economic status	low vs. verylow	1533	1038	3.88	3.58	0.46	1.6e-02*	[0.03, 0.12]	negligible
4	economic status	high vs. low	5673	1533	3.68	3.88	0.52	4.2e-02*	[-0.08, -0.01]	negligible
5	economic status	high vs. medium	5673	6812	3.68	3.58	0.49	5.4e-02	n/c	n/c
6	economic status	high vs. verylow	5673	1038	3.68	3.58	0.49	6.5e-01	n/c	n/c
7	economic status	medium vs. verylow	6812	1038	3.58	3.58	0.50	8.6e-01	n/c	n/c
8	economic status	high vs. veryhigh	5673	1974	3.68	3.54	0.49	8.8e-01	n/c	n/c
9	economic status	veryhigh vs. verylow	1974	1038	3.54	3.58	0.49	1.1e+00	n/c	n/c
10	economic status	medium vs. veryhigh	6812	1974	3.58	3.54	0.50	1.5e+00	n/c	n/c
11	household type	3mA vs. SP	3487	218	3.50	3.95	0.58	2.9e-03**	[-0.22, -0.08]	small
12	household type	2Ay3060 vs. SP	3049	218	3.27	3.95	0.61	3.0e-03**	[-0.29, -0.14]	small
13	household type	2Ay3060 vs. 3mA	3049	3487	3.27	3.50	0.53	3.1e-03**	[-0.09, -0.03]	negligible
14	household type	2Ay3060 vs. 2Ay60p	3049	2684	3.27	3.50	0.53	3.2e-03**	[-0.09, -0.03]	negligible
15	household type	2Ay1830 vs. SP	427	218	3.21	3.95	0.61	3.3e-03**	[-0.31, -0.14]	small
16	household type	2A1mCu6 vs. 3mA	1604	3487	4.14	3.50	0.43	3.4e-03**	[0.11, 0.18]	small
17	household type	2A1mCu6 vs. 2Ay60p	1604	2684	4.14	3.50	0.43	3.5e-03**	[0.11, 0.18]	small
18	household type	2A1mCu6 vs. 2Ay3060	1604	3049	4.14	3.27	0.40	3.6e-03**	[0.17, 0.24]	small
19	household type	2A1mCu6 vs. 2Ay1830	1604	427	4.14	3.21	0.39	3.7e-03**	[0.16, 0.27]	small
20	household type	2A1mCu18 vs. 3mA	1740	3487	3.89	3.50	0.45	3.8e-03**	[0.07, 0.13]	negligible
21	household type	2A1mCu18 vs. 2Ay60p	1740	2684	3.89	3.50	0.45	3.9e-03**	[0.06, 0.13]	negligible
22	household type	2A1mCu18 vs. 2Ay3060	1740	3049	3.89	3.27	0.42	4.0e-03**	[0.13, 0.19]	small
23	household type	2A1mCu18 vs. 2Ay1830	1740	427	3.89	3.21	0.41	4.1e-03**	[0.11, 0.23]	small
24	household type	2A1mCu14 vs. 3mA	2609	3487	4.15	3.50	0.43	4.2e-03**	[0.12, 0.18]	small
25	household type	2A1mCu14 vs. 2Ay60p	2609	2684	4.15	3.50	0.43	4.3e-03**	[0.12, 0.18]	small
26	household type	2A1mCu14 vs. 2Ay3060	2609	3049	4.15	3.27	0.39	4.4e-03**	[0.18, 0.24]	small
27	household type	2A1mCu14 vs. 2Ay1830	2609	427	4.15	3.21	0.39	4.5e-03**	[0.17, 0.27]	small
28	household type	1A60p vs. SP	477	218	3.28	3.95	0.60	4.6e-03**	[-0.29, -0.11]	small
29	household type	1A60p vs. 2A1mCu6	477	1604	3.28	4.14	0.60	4.7e-03**	[-0.24, -0.14]	small
30	household type	1A60p vs. 2A1mCu18	477	1740	3.28	3.89	0.57	4.8e-03**	[-0.20, -0.09]	small
31	household type	1A60p vs. 2A1mCu14	477	2609	3.28	4.15	0.60	4.9e-03**	[-0.24, -0.14]	small
32	household type	1A3060 vs. SP	600	218	3.15	3.95	0.62	5.0e-03**	[-0.33, -0.16]	small
33	household type	1A3060 vs. 2A1mCu6	600	1604	3.15	4.14	0.62	5.1e-03**	[-0.29, -0.19]	small
34	household type	1A3060 vs. 2A1mCu18	600	1740	3.15	3.89	0.60	5.2e-03**	[-0.24, -0.14]	small
35	household type	2Ay60p vs. SP	2684	218	3.50	3.95	0.57	5.2e-03**	[-0.22, -0.07]	small
36	household type	1A3060 vs. 2A1mCu14	600	2609	3.15	4.15	0.62	5.3e-03**	[-0.29, -0.20]	small
37	household type	1A1830 vs. 2A1mCu6	85	1604	3.16	4.14	0.61	5.4e-03**	[-0.33, -0.11]	small
38	household type	1A3060 vs. 3mA	600	3487	3.15	3.50	0.54	5.4e-03**	[-0.13, -0.04]	negligible
39	household type	1A1830 vs. 2A1mCu14	85	2609	3.16	4.15	0.62	5.5e-03**	[-0.34, -0.12]	small
40	household type	1A3060 vs. 2Ay60p	600	2684	3.15	3.50	0.55	5.6e-03**	[-0.14, -0.04]	negligible
41	household type	1A1830 vs. SP	85	218	3.16	3.95	0.62	2.0e-02*	[-0.37, -0.10]	small
42	household type	2A1mCu14 vs. 2A1mCu18	2609	1740	4.15	3.89	0.47	6.9e-02	n/c	n/c
43	household type	1A1830 vs. 2A1mCu18	85	1740	3.16	3.89	0.59	7.2e-02	n/c	n/c
44	household type	2Ay1830 vs. 3mA	427	3487	3.21	3.50	0.53	2.4e-01	n/c	n/c
45	household type	2Ay1830 vs. 2Ay60p	427	2684	3.21	3.50	0.53	2.5e-01	n/c	n/c
46	household type	2A1mCu18 vs. 2A1mCu6	1740	1604	3.89	4.14	0.52	2.6e-01	n/c	n/c
47	household type	2Ay60p vs. 3mA	2684	3487	3.50	3.50	0.50	9.9e-01	n/c	n/c
48	household type	1A1830 vs. 1A3060	85	600	3.16	3.15	0.50	1.9e+00	n/c	n/c
49	household type	1A60p vs. 3mA	477	3487	3.28	3.50	0.52	2.2e+00	n/c	n/c
50	household type	1A3060 vs. 1A60p	600	477	3.15	3.28	0.53	2.3e+00	n/c	n/c
51	household type	1A60p vs. 2Ay60p	477	2684	3.28	3.50	0.52	2.3e+00	n/c	n/c
52	household type	1A1830 vs. 3mA	85	3487	3.16	3.50	0.54	2.6e+00	n/c	n/c
53	household type	1A1830 vs. 2Ay60p	85	2684	3.16	3.50	0.54	2.7e+00	n/c	n/c
54	household type	2A1mCu6 vs. SP	1604	218	4.14	3.95	0.50	2.7e+00	n/c	n/c
55	household type	1A3060 vs. 2Ay3060	600	3049	3.15	3.27	0.52	2.8e+00	n/c	n/c
56	household type	2A1mCu18 vs. SP	1740	218	3.89	3.95	0.52	3.0e+00	n/c	n/c
57	household type	2A1mCu14 vs. 2A1mCu6	2609	1604	4.15	4.14	0.50	3.4e+00	n/c	n/c
58	household type	2A1mCu14 vs. SP	2609	218	4.15	3.95	0.50	4.2e+00	n/c	n/c
59	household type	1A3060 vs. 2Ay1830	600	427	3.15	3.21	0.51	4.8e+00	n/c	n/c
60	household type	1A60p vs. 2Ay3060	477	3049	3.28	3.27	0.49	4.8e+00	n/c	n/c
61	household type	1A60p vs. 2Ay1830	477	427	3.28	3.21	0.48	4.9e+00	n/c	n/c
62	household type	1A1830 vs. 2Ay1830	85	427	3.16	3.21	0.51	5.0e+00	n/c	n/c
63	household type	1A1830 vs. 1A60p	85	477	3.16	3.28	0.52	5.1e+00	n/c	n/c
64	household type	2Ay1830 vs. 2Ay3060	427	3049	3.21	3.27	0.50	5.2e+00	n/c	n/c
65	household type	1A1830 vs. 2Ay3060	85	3049	3.16	3.27	0.51	5.7e+00	n/c	n/c
66	household type, combined	1-3A vs. 2A1mCu6-18+SP	10809	6171	3.39	4.06	0.58	1e-04***	[-0.18, -0.14]	small

Significance codes: 0.0 < p*** ≤ 0.001 < p** ≤ 0.01 < p* ≤ 0.05
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 45: Vehicle level (Cliff's Method): interaction effects on number of trips per (use) day controlling for weekday = workday (II)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
67	occupation	homemaker vs. student	1201	310	4.22	3.60	0.42	1.2e-03**	[0.08, 0.22]	small
68	occupation	homemaker vs. pensioner	1201	3335	4.22	3.51	0.42	1.3e-03**	[0.13, 0.21]	small
69	occupation	halftime vs. student	3105	310	4.17	3.60	0.42	1.4e-03**	[0.09, 0.23]	small
70	occupation	halftime vs. pensioner	3105	3335	4.17	3.51	0.41	1.5e-03**	[0.15, 0.21]	small
71	occupation	fulltime vs. unemployed	7714	424	3.34	3.87	0.58	1.6e-03**	[-0.21, -0.10]	small
72	occupation	fulltime vs. pensioner	7714	3335	3.34	3.51	0.53	1.7e-03**	[-0.07, -0.03]	negligible
73	occupation	fulltime vs. homemaker	7714	1201	3.34	4.22	0.61	1.8e-03**	[-0.25, -0.18]	small
74	occupation	fulltime vs. halftime	7714	3105	3.34	4.17	0.62	1.9e-03**	[-0.26, -0.21]	small
75	occupation	apprentice vs. homemaker	432	1201	3.47	4.22	0.59	2.0e-03**	[-0.25, -0.13]	small
76	occupation	apprentice vs. halftime	432	3105	3.47	4.17	0.60	2.1e-03**	[-0.26, -0.15]	small
77	occupation	pensioner vs. unemployed	3335	424	3.51	3.87	0.55	4.4e-03**	[-0.16, -0.05]	small
78	occupation	apprentice vs. unemployed	432	424	3.47	3.87	0.56	2.0e-02*	[-0.20, -0.05]	small
79	occupation	halftime vs. unemployed	3105	424	4.17	3.87	0.46	4.5e-02*	[0.03, 0.14]	negligible
80	occupation	homemaker vs. unemployed	1201	424	4.22	3.87	0.46	1.5e-01	n/c	n/c
81	occupation	student vs. unemployed	310	424	3.60	3.87	0.54	3.4e-01	n/c	n/c
82	occupation	fulltime vs. student	7714	310	3.34	3.60	0.53	4.0e-01	n/c	n/c
83	occupation	halftime vs. homemaker	3105	1201	4.17	4.22	0.50	7.8e-01	n/c	n/c
84	occupation	apprentice vs. pensioner	432	3335	3.47	3.51	0.51	1.4e+00	n/c	n/c
85	occupation	pensioner vs. student	3335	310	3.51	3.60	0.51	1.4e+00	n/c	n/c
86	occupation	apprentice vs. fulltime	432	7714	3.47	3.34	0.49	1.6e+00	n/c	n/c
87	occupation	apprentice vs. student	432	310	3.47	3.60	0.52	1.7e+00	n/c	n/c
88	place of residence	city vs. urban	4020	8642	3.49	3.71	0.53	3.0e-04***	[-0.07, -0.03]	negligible
89	place of residence	city vs. rural	4020	4368	3.49	3.62	0.52	8.0e-03**	[-0.06, -0.01]	negligible
90	place of residence	rural vs. urban	4368	8642	3.62	3.71	0.51	7.3e-02	n/c	n/c
91	season	spring vs. summer	3678	3513	3.74	3.54	0.48	1.8e-03**	[0.02, 0.07]	negligible
92	season	spring vs. winter	3678	5224	3.74	3.62	0.49	9.5e-02	n/c	n/c
93	season	fall vs. summer	4615	3513	3.63	3.54	0.49	1.1e-01	n/c	n/c
94	season	summer vs. winter	3513	5224	3.54	3.62	0.51	2.2e-01	n/c	n/c
95	season	fall vs. spring	4615	3678	3.63	3.74	0.51	2.9e-01	n/c	n/c
96	season	fall vs. winter	4615	5224	3.63	3.62	0.50	4.9e-01	n/c	n/c
97	vehicle use freq.	daily vs. weekly	10690	2636	3.90	3.35	0.43	2.0e-04***	[0.12, 0.17]	small
98	vehicle use freq.	daily vs. rarely	10690	123	3.90	3.06	0.39	3.0e-04***	[0.13, 0.30]	small
99	vehicle use freq.	rarely vs. weekly	123	2636	3.06	3.35	0.53	1.8e-01	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 46: Vehicle level (Cliff's Method): interaction effects on number of trips per (use) day controlling for weekday = Saturday (I)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	veryhigh vs. verylow	365	202	3.79	3.24	0.45	3.3e-01	n/c	n/c
2	economic status	high vs. verylow	922	202	3.58	3.24	0.46	6.8e-01	n/c	n/c
3	economic status	medium vs. veryhigh	1136	365	3.44	3.79	0.53	6.9e-01	n/c	n/c
4	economic status	high vs. low	922	256	3.58	3.50	0.49	7.9e-01	n/c	n/c
5	economic status	low vs. medium	256	1136	3.50	3.44	0.49	1.1e+00	n/c	n/c
6	economic status	high vs. medium	922	1136	3.58	3.44	0.48	1.1e+00	n/c	n/c
7	economic status	medium vs. verylow	1136	202	3.44	3.24	0.48	1.2e+00	n/c	n/c
8	economic status	low vs. verylow	256	202	3.50	3.24	0.47	1.4e+00	n/c	n/c
9	economic status	low vs. veryhigh	256	365	3.50	3.79	0.52	1.6e+00	n/c	n/c
10	economic status	high vs. veryhigh	922	365	3.58	3.79	0.52	1.9e+00	n/c	n/c
11	household type	2A1mCu6 vs. 2Ay60p	267	509	3.60	3.06	0.42	5.0e-03**	[0.08, 0.25]	small
12	household type	2A1mCu18 vs. 2Ay60p	296	509	4.07	3.06	0.39	5.1e-03**	[0.14, 0.31]	small
13	household type	2A1mCu14 vs. 3mA	460	563	3.95	3.55	0.43	5.2e-03**	[0.07, 0.21]	small
14	household type	2A1mCu14 vs. 2Ay60p	460	509	3.95	3.06	0.38	5.3e-03**	[0.17, 0.31]	small
15	household type	1A60p vs. 2A1mCu18	89	296	2.88	4.07	0.64	5.4e-03**	[-0.40, -0.16]	small
16	household type	1A60p vs. 2A1mCu14	89	460	2.88	3.95	0.65	5.5e-03**	[-0.41, -0.19]	medium
17	household type	2A1mCu14 vs. 2Ay1830	460	68	3.95	3.06	0.38	1.9e-02*	[0.11, 0.36]	small
18	household type	1A60p vs. 2A1mCu6	89	267	2.88	3.60	0.62	2.0e-02*	[-0.36, -0.11]	small
19	household type	2A1mCu14 vs. 2Ay3060	460	475	3.95	3.46	0.44	3.3e-02*	[0.05, 0.20]	small
20	household type	2Ay3060 vs. 2Ay60p	475	509	3.46	3.06	0.44	4.6e-02*	[0.05, 0.19]	small
21	household type	2A1mCu18 vs. 3mA	296	563	4.07	3.55	0.43	8.8e-02	n/c	n/c
22	household type	2A1mCu18 vs. 2Ay1830	296	68	4.07	3.06	0.39	9.0e-02	n/c	n/c
23	household type	1A60p vs. 2Ay3060	89	475	2.88	3.46	0.59	1.3e-01	n/c	n/c
24	household type	1A3060 vs. 2A1mCu14	91	460	3.22	3.95	0.59	1.7e-01	n/c	n/c
25	household type	2A1mCu18 vs. 2Ay3060	296	475	4.07	3.46	0.44	2.5e-01	n/c	n/c
26	household type	2Ay60p vs. 3mA	509	563	3.06	3.55	0.54	3.5e-01	n/c	n/c
27	household type	1A3060 vs. 2A1mCu18	91	296	3.22	4.07	0.58	3.6e-01	n/c	n/c
28	household type	1A60p vs. 3mA	89	563	2.88	3.55	0.57	3.8e-01	n/c	n/c
29	household type	2A1mCu6 vs. 2Ay1830	267	68	3.60	3.06	0.42	8.9e-01	n/c	n/c
30	household type	2A1mCu14 vs. 2A1mCu18	460	296	3.95	4.07	0.50	9.9e-01	n/c	n/c
31	household type	1A3060 vs. 1A60p	91	89	3.22	2.88	0.42	1.9e+00	n/c	n/c
32	household type	3mA vs. SP	563	44	3.55	3.30	0.50	1.9e+00	n/c	n/c
33	household type	2A1mCu14 vs. SP	460	44	3.95	3.30	0.42	1.9e+00	n/c	n/c
34	household type	2A1mCu18 vs. SP	296	44	4.07	3.30	0.43	2.3e+00	n/c	n/c
35	household type	2A1mCu14 vs. 2A1mCu6	460	267	3.95	3.60	0.46	2.4e+00	n/c	n/c
36	household type	1A60p vs. SP	89	44	2.88	3.30	0.59	2.5e+00	n/c	n/c
37	household type	1A1830 vs. 2Ay3060	11	475	3.27	3.46	0.49	2.8e+00	n/c	n/c
38	household type	2A1mCu6 vs. 3mA	267	563	3.60	3.55	0.47	2.9e+00	n/c	n/c
39	household type	2Ay1830 vs. 2Ay3060	68	475	3.06	3.46	0.55	3.5e+00	n/c	n/c
40	household type	1A3060 vs. SP	91	44	3.22	3.30	0.51	3.5e+00	n/c	n/c
41	household type	2A1mCu18 vs. 2A1mCu6	296	267	4.07	3.60	0.46	3.6e+00	n/c	n/c
42	household type	1A3060 vs. 2A1mCu6	91	267	3.22	3.60	0.55	4.0e+00	n/c	n/c
43	household type	1A3060 vs. 2Ay60p	91	509	3.22	3.06	0.46	4.2e+00	n/c	n/c
44	household type	1A1830 vs. 1A60p	11	89	3.27	2.88	0.38	4.2e+00	n/c	n/c
45	household type	1A3060 vs. 3mA	91	563	3.22	3.55	0.51	4.2e+00	n/c	n/c
46	household type	2Ay1830 vs. 2Ay60p	68	509	3.06	3.06	0.49	5.0e+00	n/c	n/c
47	household type	2Ay60p vs. SP	509	44	3.06	3.30	0.55	5.2e+00	n/c	n/c
48	household type	2Ay3060 vs. SP	475	44	3.46	3.30	0.49	5.5e+00	n/c	n/c
49	household type	2A1mCu6 vs. 2Ay3060	267	475	3.60	3.46	0.47	5.8e+00	n/c	n/c
50	household type	2Ay1830 vs. 3mA	68	563	3.06	3.55	0.54	5.8e+00	n/c	n/c
51	household type	1A60p vs. 2Ay60p	89	509	2.88	3.06	0.53	6.2e+00	n/c	n/c
52	household type	2Ay3060 vs. 3mA	475	563	3.46	3.55	0.49	6.2e+00	n/c	n/c
53	household type	1A1830 vs. 2A1mCu14	11	460	3.27	3.95	0.57	6.3e+00	n/c	n/c
54	household type	1A1830 vs. 2A1mCu18	11	296	3.27	4.07	0.56	6.3e+00	n/c	n/c
55	household type	2Ay1830 vs. SP	68	44	3.06	3.30	0.54	6.3e+00	n/c	n/c
56	household type	1A1830 vs. 2Ay1830	11	68	3.27	3.06	0.43	6.3e+00	n/c	n/c
57	household type	1A1830 vs. SP	11	44	3.27	3.30	0.48	6.3e+00	n/c	n/c
58	household type	1A60p vs. 2Ay1830	89	68	2.88	3.06	0.55	6.4e+00	n/c	n/c
59	household type	1A1830 vs. 2Ay60p	11	509	3.27	3.06	0.43	6.5e+00	n/c	n/c
60	household type	1A3060 vs. 2Ay1830	91	68	3.22	3.06	0.46	6.6e+00	n/c	n/c
61	household type	2A1mCu6 vs. SP	267	44	3.60	3.30	0.46	6.6e+00	n/c	n/c
62	household type	1A1830 vs. 3mA	11	563	3.27	3.55	0.48	6.8e+00	n/c	n/c
63	household type	1A3060 vs. 2Ay3060	91	475	3.22	3.46	0.52	6.8e+00	n/c	n/c
64	household type	1A1830 vs. 1A3060	11	91	3.27	3.22	0.47	7.4e+00	n/c	n/c
65	household type	1A1830 vs. 2A1mCu6	11	267	3.27	3.60	0.53	8.0e+00	n/c	n/c
66	household type, combined	1-3A vs. 2A1mCu6-18+SP	1806	1067	3.32	3.87	0.58	1e-04***	[-0.19, -0.11]	small

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 47: Vehicle level (Cliff's Method): interaction effects on number of trips per (use) day controlling for weekday = Saturday (II)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
67	occupation	homemaker vs. pensioner	169	636	3.91	3.06	0.38	1.9e-03**	[0.13, 0.32]	small
68	occupation	halftime vs. pensioner	438	636	3.81	3.06	0.40	2.0e-03**	[0.13, 0.26]	small
69	occupation	fulltime vs. pensioner	1341	636	3.50	3.06	0.45	2.1e-03**	[0.05, 0.15]	small
70	occupation	fulltime vs. halftime	1341	438	3.50	3.81	0.54	9.0e-02	n/c	n/c
71	occupation	pensioner vs. unemployed	636	75	3.06	4.00	0.60	1.0e-01	n/c	n/c
72	occupation	apprentice vs. pensioner	65	636	4.00	3.06	0.39	1.3e-01	n/c	n/c
73	occupation	fulltime vs. homemaker	1341	169	3.50	3.91	0.56	1.4e-01	n/c	n/c
74	occupation	pensioner vs. student	636	61	3.06	3.57	0.59	3.1e-01	n/c	n/c
75	occupation	apprentice vs. unemployed	65	75	4.00	4.00	0.50	9.6e-01	n/c	n/c
76	occupation	fulltime vs. unemployed	1341	75	3.50	4.00	0.55	1.8e+00	n/c	n/c
77	occupation	apprentice vs. homemaker	65	169	4.00	3.91	0.50	1.9e+00	n/c	n/c
78	occupation	apprentice vs. fulltime	65	1341	4.00	3.50	0.45	1.9e+00	n/c	n/c
79	occupation	homemaker vs. unemployed	169	75	3.91	4.00	0.49	2.6e+00	n/c	n/c
80	occupation	halftime vs. unemployed	438	75	3.81	4.00	0.51	3.3e+00	n/c	n/c
81	occupation	apprentice vs. halftime	65	438	4.00	3.81	0.49	3.9e+00	n/c	n/c
82	occupation	fulltime vs. student	1341	61	3.50	3.57	0.53	4.2e+00	n/c	n/c
83	occupation	student vs. unemployed	61	75	3.57	4.00	0.52	4.5e+00	n/c	n/c
84	occupation	halftime vs. student	438	61	3.81	3.57	0.49	4.5e+00	n/c	n/c
85	occupation	halftime vs. homemaker	438	169	3.81	3.91	0.52	4.8e+00	n/c	n/c
86	occupation	homemaker vs. student	169	61	3.91	3.57	0.47	4.9e+00	n/c	n/c
87	occupation	apprentice vs. student	65	61	4.00	3.57	0.47	5.0e+00	n/c	n/c
88	place of residence	rural vs. urban	769	1440	3.38	3.64	0.53	7.2e-02	n/c	n/c
89	place of residence	city vs. urban	672	1440	3.42	3.64	0.51	3.5e-01	n/c	n/c
90	place of residence	city vs. rural	672	769	3.42	3.38	0.48	5.4e-01	n/c	n/c
91	season	spring vs. summer	680	605	3.62	3.48	0.48	7.5e-01	n/c	n/c
92	season	spring vs. winter	680	799	3.62	3.43	0.48	7.8e-01	n/c	n/c
93	season	summer vs. winter	605	799	3.48	3.43	0.50	9.7e-01	n/c	n/c
94	season	fall vs. winter	797	799	3.56	3.43	0.49	1.1e+00	n/c	n/c
95	season	fall vs. spring	797	680	3.56	3.62	0.51	1.4e+00	n/c	n/c
96	season	fall vs. summer	797	605	3.56	3.48	0.49	1.6e+00	n/c	n/c
97	vehicle use freq.	daily vs. weekly	1834	472	3.80	3.20	0.42	3.0e-04***	[0.11, 0.21]	small
98	vehicle use freq.	daily vs. rarely	1834	28	3.80	2.68	0.35	4.0e-03**	[0.12, 0.47]	medium
99	vehicle use freq.	rarely vs. weekly	28	472	2.68	3.20	0.58	1.4e-01	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 48: Vehicle level (Cliff's Method): interaction effects on number of trips per (use) day controlling for weekday = Sunday (I)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	economic status	low vs. medium	204	829	3.05	2.58	0.42	5.0e-03**	[0.07, 0.24]	small
2	economic status	high vs. medium	720	829	2.74	2.58	0.47	2.2e-01	n/c	n/c
3	economic status	low vs. verylow	204	121	3.05	2.60	0.43	2.2e-01	n/c	n/c
4	economic status	low vs. veryhigh	204	267	3.05	2.69	0.45	2.4e-01	n/c	n/c
5	economic status	high vs. low	720	204	2.74	3.05	0.55	2.5e-01	n/c	n/c
6	economic status	medium vs. veryhigh	829	267	2.58	2.69	0.53	8.0e-01	n/c	n/c
7	economic status	high vs. veryhigh	720	267	2.74	2.69	0.50	8.3e-01	n/c	n/c
8	economic status	high vs. verylow	720	121	2.74	2.60	0.48	1.6e+00	n/c	n/c
9	economic status	medium vs. verylow	829	121	2.58	2.60	0.51	1.6e+00	n/c	n/c
10	economic status	veryhigh vs. verylow	267	121	2.69	2.60	0.48	1.6e+00	n/c	n/c
11	household type	2A1mCu18 vs. 2Ay1830	230	72	2.93	2.29	0.38	3.2e-02*	[0.11, 0.37]	small
12	household type	2A1mCu14 vs. 2Ay1830	313	72	2.89	2.29	0.37	3.3e-02*	[0.11, 0.38]	small
13	household type	2Ay1830 vs. 3mA	72	425	2.29	2.83	0.61	1.1e-01	n/c	n/c
14	household type	2A1mCu14 vs. 2Ay3060	313	348	2.89	2.57	0.44	2.1e-01	n/c	n/c
15	household type	2A1mCu14 vs. 2Ay60p	313	331	2.89	2.56	0.44	3.6e-01	n/c	n/c
16	household type	2A1mCu18 vs. 2Ay60p	230	331	2.93	2.56	0.44	8.6e-01	n/c	n/c
17	household type	2A1mCu18 vs. 2Ay3060	230	348	2.93	2.57	0.44	8.8e-01	n/c	n/c
18	household type	1A60p vs. 2A1mCu14	47	313	2.36	2.89	0.59	9.0e-01	n/c	n/c
19	household type	1A1830 vs. 2Ay1830	13	72	2.38	2.29	0.49	9.6e-01	n/c	n/c
20	household type	1A60p vs. 2A1mCu18	47	230	2.36	2.93	0.59	1.0e+00	n/c	n/c
21	household type	2Ay3060 vs. 3mA	348	425	2.57	2.83	0.54	1.4e+00	n/c	n/c
22	household type	2A1mCu6 vs. 2Ay1830	245	72	2.64	2.29	0.42	1.4e+00	n/c	n/c
23	household type	1A3060 vs. 2A1mCu14	81	313	2.47	2.89	0.57	1.4e+00	n/c	n/c
24	household type	2Ay60p vs. 3mA	331	425	2.56	2.83	0.54	1.8e+00	n/c	n/c
25	household type	1A3060 vs. 2A1mCu18	81	230	2.47	2.93	0.56	1.8e+00	n/c	n/c
26	household type	2A1mCu14 vs. 2A1mCu6	313	245	2.89	2.64	0.45	1.8e+00	n/c	n/c
27	household type	1A60p vs. 3mA	47	425	2.36	2.83	0.57	1.9e+00	n/c	n/c
28	household type	2A1mCu14 vs. 2A1mCu18	313	230	2.89	2.93	0.50	1.9e+00	n/c	n/c
29	household type	2Ay1830 vs. 2Ay60p	72	331	2.29	2.56	0.57	2.0e+00	n/c	n/c
30	household type	2Ay1830 vs. 2Ay3060	72	348	2.29	2.57	0.57	2.2e+00	n/c	n/c
31	household type	2A1mCu18 vs. 2A1mCu6	230	245	2.93	2.64	0.45	2.6e+00	n/c	n/c
32	household type	2Ay3060 vs. 2Ay60p	348	331	2.57	2.56	0.50	2.8e+00	n/c	n/c
33	household type	2A1mCu6 vs. SP	245	30	2.64	2.70	0.51	3.6e+00	n/c	n/c
34	household type	1A3060 vs. 3mA	81	425	2.47	2.83	0.55	3.9e+00	n/c	n/c
35	household type	1A3060 vs. 2Ay1830	81	72	2.47	2.29	0.43	4.0e+00	n/c	n/c
36	household type	1A3060 vs. 2Ay3060	81	348	2.47	2.57	0.50	4.5e+00	n/c	n/c
37	household type	1A3060 vs. 2Ay60p	81	331	2.47	2.56	0.51	5.2e+00	n/c	n/c
38	household type	2Ay60p vs. SP	331	30	2.56	2.70	0.52	5.3e+00	n/c	n/c
39	household type	2Ay3060 vs. SP	348	30	2.57	2.70	0.52	5.8e+00	n/c	n/c
40	household type	2Ay1830 vs. SP	72	30	2.29	2.70	0.58	5.8e+00	n/c	n/c
41	household type	2A1mCu6 vs. 3mA	245	425	2.64	2.83	0.53	5.9e+00	n/c	n/c
42	household type	1A1830 vs. 1A60p	13	47	2.38	2.36	0.54	6.5e+00	n/c	n/c
43	household type	1A1830 vs. 2A1mCu18	13	230	2.38	2.93	0.61	6.5e+00	n/c	n/c
44	household type	1A1830 vs. 2A1mCu14	13	313	2.38	2.89	0.61	6.7e+00	n/c	n/c
45	household type	1A3060 vs. SP	81	30	2.47	2.70	0.52	7.0e+00	n/c	n/c
46	household type	3mA vs. SP	425	30	2.83	2.70	0.48	7.6e+00	n/c	n/c
47	household type	1A60p vs. 2A1mCu6	47	245	2.36	2.64	0.54	7.8e+00	n/c	n/c
48	household type	2A1mCu6 vs. 2Ay60p	245	331	2.64	2.56	0.49	7.9e+00	n/c	n/c
49	household type	1A3060 vs. 2A1mCu6	81	245	2.47	2.64	0.52	7.9e+00	n/c	n/c
50	household type	1A3060 vs. 1A60p	81	47	2.47	2.36	0.47	8.0e+00	n/c	n/c
51	household type	1A1830 vs. 3mA	13	425	2.38	2.83	0.60	8.1e+00	n/c	n/c
52	household type	2A1mCu6 vs. 2Ay3060	245	348	2.64	2.57	0.49	8.3e+00	n/c	n/c
53	household type	1A1830 vs. 1A3060	13	81	2.38	2.47	0.56	8.3e+00	n/c	n/c
54	household type	2A1mCu18 vs. SP	230	30	2.93	2.70	0.46	8.5e+00	n/c	n/c
55	household type	1A1830 vs. 2Ay60p	13	331	2.38	2.56	0.56	9.0e+00	n/c	n/c
56	household type	1A1830 vs. 2Ay3060	13	348	2.38	2.57	0.56	9.5e+00	n/c	n/c
57	household type	2A1mCu14 vs. SP	313	30	2.89	2.70	0.46	9.8e+00	n/c	n/c
58	household type	1A1830 vs. SP	13	30	2.38	2.70	0.58	9.9e+00	n/c	n/c
59	household type	2A1mCu18 vs. 3mA	230	425	2.93	2.83	0.48	1.0e+01	n/c	n/c
60	household type	1A60p vs. SP	47	30	2.36	2.70	0.55	1.0e+01	n/c	n/c
61	household type	1A1830 vs. 2A1mCu6	13	245	2.38	2.64	0.57	1.1e+01	n/c	n/c
62	household type	2A1mCu14 vs. 3mA	313	425	2.89	2.83	0.48	1.1e+01	n/c	n/c
63	household type	1A60p vs. 2Ay60p	47	331	2.36	2.56	0.53	1.1e+01	n/c	n/c
64	household type	1A60p vs. 2Ay3060	47	348	2.36	2.57	0.53	1.1e+01	n/c	n/c
65	household type	1A60p vs. 2Ay1830	47	72	2.36	2.29	0.46	1.1e+01	n/c	n/c
66	household type, combined	1-3A vs. 2A1mCu6-18+SP	1317	818	2.62	2.82	0.54	4e-03**	[-0.12, -0.02]	negligible

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Table 49: Vehicle level (Cliff's Method): interaction effects on number of trips per (use) day controlling for weekday = Sunday (II)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
67	occupation	halftime vs. pensioner	287	413	2.89	2.55	0.44	6.3e-02	n/c	n/c
68	occupation	fulltime vs. halftime	1074	287	2.65	2.89	0.55	1.8e-01	n/c	n/c
69	occupation	homemaker vs. pensioner	118	413	2.85	2.55	0.44	4.2e-01	n/c	n/c
70	occupation	fulltime vs. homemaker	1074	118	2.65	2.85	0.55	9.5e-01	n/c	n/c
71	occupation	halftime vs. homemaker	287	118	2.89	2.85	0.50	9.9e-01	n/c	n/c
72	occupation	student vs. unemployed	47	55	2.57	2.53	0.50	2.0e+00	n/c	n/c
73	occupation	halftime vs. unemployed	287	55	2.89	2.53	0.44	2.7e+00	n/c	n/c
74	occupation	pensioner vs. student	413	47	2.55	2.57	0.50	2.8e+00	n/c	n/c
75	occupation	homemaker vs. unemployed	118	55	2.85	2.53	0.44	3.2e+00	n/c	n/c
76	occupation	halftime vs. student	287	47	2.89	2.57	0.44	3.3e+00	n/c	n/c
77	occupation	pensioner vs. unemployed	413	55	2.55	2.53	0.51	3.4e+00	n/c	n/c
78	occupation	homemaker vs. student	118	47	2.85	2.57	0.44	3.5e+00	n/c	n/c
79	occupation	fulltime vs. unemployed	1074	55	2.65	2.53	0.49	4.2e+00	n/c	n/c
80	occupation	fulltime vs. student	1074	47	2.65	2.57	0.49	5.0e+00	n/c	n/c
81	occupation	fulltime vs. pensioner	1074	413	2.65	2.55	0.49	5.1e+00	n/c	n/c
82	occupation	apprentice vs. fulltime	62	1074	2.87	2.65	0.49	5.1e+00	n/c	n/c
83	occupation	apprentice vs. homemaker	62	118	2.87	2.85	0.53	5.4e+00	n/c	n/c
84	occupation	apprentice vs. unemployed	62	55	2.87	2.53	0.48	5.7e+00	n/c	n/c
85	occupation	apprentice vs. pensioner	62	413	2.87	2.55	0.47	5.8e+00	n/c	n/c
86	occupation	apprentice vs. halftime	62	287	2.87	2.89	0.53	6.1e+00	n/c	n/c
87	occupation	apprentice vs. student	62	47	2.87	2.57	0.48	6.1e+00	n/c	n/c
88	place of residence	city vs. rural	530	558	2.60	2.75	0.52	6.0e-01	n/c	n/c
89	place of residence	city vs. urban	530	1053	2.60	2.72	0.52	6.3e-01	n/c	n/c
90	place of residence	rural vs. urban	558	1053	2.75	2.72	0.50	9.5e-01	n/c	n/c
91	season	spring vs. summer	505	486	2.87	2.57	0.45	3.0e-02*	[0.03, 0.17]	negligible
92	season	fall vs. spring	612	505	2.64	2.87	0.54	1.6e-01	n/c	n/c
93	season	summer vs. winter	486	538	2.57	2.71	0.53	2.4e-01	n/c	n/c
94	season	fall vs. summer	612	486	2.64	2.57	0.48	3.6e-01	n/c	n/c
95	season	fall vs. winter	612	538	2.64	2.71	0.52	6.0e-01	n/c	n/c
96	season	spring vs. winter	505	538	2.87	2.71	0.48	7.8e-01	n/c	n/c
97	vehicle use freq.	rarely vs. weekly	14	340	2.00	2.69	0.68	3.8e-02*	[-0.60, -0.06]	medium
98	vehicle use freq.	daily vs. rarely	1349	14	2.79	2.00	0.31	3.9e-02*	[0.08, 0.61]	medium
99	vehicle use freq.	daily vs. weekly	1349	340	2.79	2.69	0.49	5.5e-01	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

A.4.3 Trip level

Table 50: Trip level (Cliff's method): main effects on driven distance [km] (H-W or W-H trips)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	occupation	fulltime vs. halftime	10207	3065	19.70	12.12	0.37	2.0e-03**	[0.24, 0.28]	small
2	occupation	apprentice vs. halftime	339	3065	17.07	12.12	0.40	2.1e-03**	[0.13, 0.25]	small
3	occupation	halftime vs. student	3065	106	12.12	15.15	0.58	1.9e-01	n/c	n/c
4	occupation	apprentice vs. fulltime	339	10207	17.07	19.70	0.54	2.5e-01	n/c	n/c
5	occupation	fulltime vs. student	10207	106	19.70	15.15	0.45	8.3e-01	n/c	n/c
6	occupation	apprentice vs. student	339	106	17.07	15.15	0.48	9.8e+00	n/c	n/c
7	place of residence	city vs. urban	2820	7158	16.08	17.53	0.54	2.0e-04***	[-0.11, -0.06]	negligible
8	place of residence	city vs. rural	2820	3739	16.08	20.00	0.54	3.0e-04***	[-0.11, -0.05]	negligible
9	place of residence	rural vs. urban	3739	7158	20.00	17.53	0.50	6.4e-01	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Note: it is assumed that H-W or W-H trips are only
executed by the following occupation types: fulltime, halftime, apprentice, student

Table 51: Trip level (Cliff's method): interaction effects on driven distance [km] controlling for place of residence = city (all trips except H-W or W-H trips)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	number of trips per day	5to6 vs. 7to17	3040	2341	9.13	7.01	0.46	2.0e-04***	[0.06, 0.12]	negligible
2	number of trips per day	3to4 vs. 7to17	4801	2341	10.24	7.01	0.44	3.0e-04***	[0.09, 0.14]	small
3	number of trips per day	1to2 vs. 7to17	2780	2341	21.63	7.01	0.35	4.0e-04***	[0.26, 0.32]	small
4	number of trips per day	1to2 vs. 5to6	2780	3040	21.63	9.13	0.40	5.0e-04***	[0.18, 0.24]	small
5	number of trips per day	1to2 vs. 3to4	2780	4801	21.63	10.24	0.41	6.0e-04***	[0.15, 0.21]	small
6	number of trips per day	3to4 vs. 5to6	4801	3040	10.24	9.13	0.49	3.6e-02*	[0.00, 0.05]	negligible
7	season	summer vs. winter	2258	4292	12.87	10.61	0.48	1.2e-02*	[0.02, 0.08]	negligible
8	season	spring vs. winter	2707	4292	13.20	10.61	0.48	1.1e-01	n/c	n/c
9	season	fall vs. winter	3705	4292	11.64	10.61	0.49	2.7e-01	n/c	n/c
10	season	fall vs. summer	3705	2258	11.64	12.87	0.51	3.6e-01	n/c	n/c
11	season	fall vs. spring	3705	2707	11.64	13.20	0.50	5.5e-01	n/c	n/c
12	season	spring vs. summer	2707	2258	13.20	12.87	0.51	7.2e-01	n/c	n/c
13	trip distance category	outside city vs. unknown	2762	1157	28.10	17.96	0.37	1e-04***	[0.22, 0.30]	small
14	trip distance category	inside city vs. unknown	8786	1157	5.73	17.96	0.67	2e-04***	[-0.37, -0.30]	medium
15	trip distance category	inside city vs. outside city	8786	2762	5.73	28.10	0.81	3e-04***	[-0.63, -0.60]	large
16	trip purpose	leisure vs. shopping	3990	4331	18.41	6.45	0.32	8.0e-04***	[0.34, 0.39]	medium
17	trip purpose	errand vs. shopping	2210	4331	10.40	6.45	0.40	9.0e-04***	[0.17, 0.23]	small
18	trip purpose	errand vs. leisure	2210	3990	10.40	18.41	0.59	1.0e-03***	[-0.20, -0.14]	small
19	trip purpose	education vs. shopping	155	4331	22.33	6.45	0.21	1.1e-03**	[0.50, 0.64]	large
20	trip purpose	education vs. leisure	155	3990	22.33	18.41	0.39	1.2e-03**	[0.14, 0.31]	small
21	trip purpose	education vs. errand	155	2210	22.33	10.40	0.30	1.3e-03**	[0.31, 0.47]	medium
22	trip purpose	business vs. shopping	339	4331	32.23	6.45	0.25	1.4e-03**	[0.43, 0.55]	medium
23	trip purpose	business vs. leisure	339	3990	32.23	18.41	0.41	1.5e-03**	[0.10, 0.24]	small
24	trip purpose	business vs. errand	339	2210	32.23	10.40	0.34	1.6e-03**	[0.26, 0.39]	medium
25	trip purpose	accompanying vs. shopping	1931	4331	7.57	6.45	0.45	1.7e-03**	[0.07, 0.13]	small
26	trip purpose	accompanying vs. leisure	1931	3990	7.57	18.41	0.63	1.8e-03**	[-0.30, -0.24]	small
27	trip purpose	accompanying vs. errand	1931	2210	7.57	10.40	0.55	1.9e-03**	[-0.13, -0.06]	negligible
28	trip purpose	accompanying vs. education	1931	155	7.57	22.33	0.74	2.0e-03**	[-0.56, -0.40]	medium
29	trip purpose	accompanying vs. business	1931	339	7.57	32.23	0.71	2.1e-03**	[-0.47, -0.35]	medium
30	trip purpose	business vs. education	339	155	32.23	22.33	0.52	3.4e+00	n/c	n/c
31	weekday	sunday vs. workday	1206	9800	21.25	10.42	0.40	1e-04***	[0.16, 0.23]	small
32	weekday	saturday vs. workday	1956	9800	13.17	10.42	0.47	2e-04***	[0.03, 0.09]	negligible
33	weekday	saturday vs. sunday	1956	1206	13.17	21.25	0.57	3e-04***	[-0.17, -0.09]	small

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Note: it is assumed that H-W or W-H trips are only
executed by the following occupation types: fulltime, halftime, apprentice, student

Table 52: Trip level (Cliff's method): interaction effects on driven distance [km] controlling for place of residence = rural (all trips except H-W or W-H trips)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	number of trips per day	5to6 vs. 7to17	3372	2705	9.56	6.43	0.42	1e-04***	[0.13, 0.18]	small
2	number of trips per day	3to4 vs. 7to17	4765	2705	12.02	6.43	0.38	2e-04***	[0.21, 0.26]	small
3	number of trips per day	3to4 vs. 5to6	4765	3372	12.02	9.56	0.46	3e-04***	[0.06, 0.11]	negligible
4	number of trips per day	1to2 vs. 7to17	2771	2705	23.76	6.43	0.31	4e-04***	[0.34, 0.40]	medium
5	number of trips per day	1to2 vs. 5to6	2771	3372	23.76	9.56	0.38	5e-04***	[0.20, 0.26]	small
6	number of trips per day	1to2 vs. 3to4	2771	4765	23.76	12.02	0.42	6e-04***	[0.12, 0.18]	small
7	season	fall vs. summer	3405	2895	13.02	14.02	0.53	3.0e-03**	[-0.08, -0.02]	negligible
8	season	summer vs. winter	2895	3527	14.02	11.44	0.48	5.0e-03**	[0.02, 0.08]	negligible
9	season	spring vs. summer	3786	2895	12.53	14.02	0.52	6.4e-02	n/c	n/c
10	season	fall vs. spring	3405	3786	13.02	12.53	0.51	4.8e-01	n/c	n/c
11	season	spring vs. winter	3786	3527	12.53	11.44	0.49	5.4e-01	n/c	n/c
12	season	fall vs. winter	3405	3527	13.02	11.44	0.50	7.5e-01	n/c	n/c
13	trip distance category	outside city vs. unknown	6071	1453	20.04	14.09	0.37	1e-04***	[0.23, 0.30]	small
14	trip distance category	inside city vs. unknown	5816	1453	4.56	14.09	0.71	2e-04***	[-0.44, -0.38]	medium
15	trip distance category	inside city vs. outside city	5816	6071	4.56	20.04	0.86	3e-04***	[-0.74, -0.71]	large
16	trip purpose	leisure vs. shopping	4038	4394	18.36	7.63	0.37	9.0e-04***	[0.24, 0.29]	small
17	trip purpose	errand vs. shopping	2522	4394	11.19	7.63	0.43	1.0e-03***	[0.10, 0.16]	small
18	trip purpose	errand vs. leisure	2522	4038	11.19	18.36	0.57	1.1e-03**	[-0.16, -0.10]	small
19	trip purpose	education vs. shopping	215	4394	24.46	7.63	0.21	1.2e-03**	[0.51, 0.64]	large
20	trip purpose	education vs. leisure	215	4038	24.46	18.36	0.33	1.3e-03**	[0.26, 0.40]	medium
21	trip purpose	education vs. errand	215	2522	24.46	11.19	0.27	1.4e-03**	[0.39, 0.53]	medium
22	trip purpose	business vs. shopping	315	4394	43.61	7.63	0.24	1.5e-03**	[0.46, 0.57]	large
23	trip purpose	business vs. leisure	315	4038	43.61	18.36	0.36	1.6e-03**	[0.22, 0.35]	small
24	trip purpose	business vs. errand	315	2522	43.61	11.19	0.30	1.7e-03**	[0.34, 0.47]	medium
25	trip purpose	accompanying vs. leisure	2129	4038	8.38	18.36	0.62	1.8e-03**	[-0.27, -0.22]	small
26	trip purpose	accompanying vs. errand	2129	2522	8.38	11.19	0.56	1.9e-03**	[-0.15, -0.08]	small
27	trip purpose	accompanying vs. education	2129	215	8.38	24.46	0.78	2.0e-03**	[-0.62, -0.49]	large
28	trip purpose	accompanying vs. business	2129	315	8.38	43.61	0.75	2.1e-03**	[-0.56, -0.44]	large
29	trip purpose	accompanying vs. shopping	2129	4394	8.38	7.63	0.49	2.2e+00	n/c	n/c
30	trip purpose	business vs. education	315	215	43.61	24.46	0.51	4.8e+00	n/c	n/c
31	weekday	sunday vs. workday	1225	10280	21.21	11.31	0.39	1e-04***	[0.18, 0.25]	small
32	weekday	saturday vs. workday	2108	10280	14.48	11.31	0.47	2e-04***	[0.03, 0.09]	negligible
33	weekday	saturday vs. sunday	2108	1225	14.48	21.21	0.58	3e-04***	[-0.19, -0.11]	small

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Note: it is assumed that H-W or W-H trips are only
executed by the following occupation types: fulltime, halftime, apprentice, student

Table 53: Trip level (Cliff's method): interaction effects on driven distance [km] controlling for place of residence = urban (all trips except H-W or W-H trips)

1	number of trips per day	5to6 vs. 7to17	6775	5913	8.76	6.64	0.45	1e-04***	[0.08, 0.12]	small
2	number of trips per day	3to4 vs. 7to17	9205	5913	11.50	6.64	0.41	2e-04***	[0.16, 0.20]	small
3	number of trips per day	3to4 vs. 5to6	9205	6775	11.50	8.76	0.46	3e-04***	[0.06, 0.10]	negligible
4	number of trips per day	1to2 vs. 7to17	5558	5913	19.38	6.64	0.34	4e-04***	[0.29, 0.33]	medium
5	number of trips per day	1to2 vs. 5to6	5558	6775	19.38	8.76	0.39	5e-04***	[0.19, 0.23]	small
6	number of trips per day	1to2 vs. 3to4	5558	9205	19.38	11.50	0.43	6e-04***	[0.12, 0.15]	small
7	season	summer vs. winter	5817	8234	11.95	10.68	0.48	5.0e-04***	[0.03, 0.07]	negligible
8	season	fall vs. summer	7663	5817	11.43	11.95	0.52	6.0e-04***	[-0.07, -0.03]	negligible
9	season	spring vs. summer	5737	5817	11.71	11.95	0.51	6.4e-02	n/c	n/c
10	season	spring vs. winter	5737	8234	11.71	10.68	0.49	7.5e-02	n/c	n/c
11	season	fall vs. spring	7663	5737	11.43	11.71	0.51	1.0e-01	n/c	n/c
12	season	fall vs. winter	7663	8234	11.43	10.68	0.50	7.7e-01	n/c	n/c
13	trip distance category	outside city vs. unknown	11517	3012	18.63	14.41	0.38	1e-04***	[0.21, 0.26]	small
14	trip distance category	inside city vs. unknown	12336	3012	3.70	14.41	0.74	2e-04***	[-0.50, -0.45]	medium
15	trip distance category	inside city vs. outside city	12336	11517	3.70	18.63	0.87	3e-04***	[-0.75, -0.73]	large
16	trip purpose	leisure vs. shopping	7914	9047	17.16	7.02	0.36	8.0e-04***	[0.26, 0.29]	small
17	trip purpose	errand vs. shopping	4991	9047	9.92	7.02	0.45	9.0e-04***	[0.08, 0.12]	small
18	trip purpose	errand vs. leisure	4991	7914	9.92	17.16	0.59	1.0e-03***	[-0.19, -0.15]	small
19	trip purpose	education vs. shopping	456	9047	21.42	7.02	0.19	1.1e-03**	[0.58, 0.67]	large
20	trip purpose	education vs. leisure	456	7914	21.42	17.16	0.31	1.2e-03**	[0.33, 0.43]	medium
21	trip purpose	education vs. errand	456	4991	21.42	9.92	0.23	1.3e-03**	[0.49, 0.58]	large
22	trip purpose	business vs. shopping	673	9047	29.27	7.02	0.30	1.4e-03**	[0.36, 0.45]	medium
23	trip purpose	business vs. leisure	673	7914	29.27	17.16	0.42	1.5e-03**	[0.11, 0.20]	small
24	trip purpose	business vs. errand	673	4991	29.27	9.92	0.34	1.6e-03**	[0.26, 0.36]	medium
25	trip purpose	business vs. education	673	456	29.27	21.42	0.60	1.7e-03**	[-0.26, -0.13]	small
26	trip purpose	accompanying vs. leisure	4368	7914	7.78	17.16	0.62	1.8e-03**	[-0.27, -0.23]	small
27	trip purpose	accompanying vs. errand	4368	4991	7.78	9.92	0.54	1.9e-03**	[-0.10, -0.05]	negligible
28	trip purpose	accompanying vs. education	4368	456	7.78	21.42	0.80	2.0e-03**	[-0.64, -0.55]	large
29	trip purpose	accompanying vs. business	4368	673	7.78	29.27	0.69	2.1e-03**	[-0.42, -0.33]	medium
30	trip purpose	accompanying vs. shopping	4368	9047	7.78	7.02	0.49	7.7e-02	n/c	n/c
31	weekday	sunday vs. workday	2420	20890	19.01	10.15	0.42	2e-04***	[0.14, 0.19]	small
32	weekday	saturday vs. sunday	4141	2420	13.07	19.01	0.56	3e-04***	[-0.15, -0.10]	small
33	weekday	saturday vs. workday	4141	20890	13.07	10.15	0.48	5e-04***	[0.02, 0.05]	negligible

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Note: it is assumed that H-W or W-H trips are only
executed by the following occupation types: fulltime, halftime, apprentice, student

Table 54: Trip level (Cliff's method): main effects on departure time [5min] (first H-W trips per day)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	occupation	fulltime vs. student	4898	47	85.94	106.49	0.68	1.9e-03**	[-0.52, -0.19]	medium
2	occupation	fulltime vs. halftime	4898	1382	85.94	96.08	0.66	2.0e-03**	[-0.36, -0.29]	medium
3	occupation	apprentice vs. halftime	147	1382	89.13	96.08	0.64	2.1e-03**	[-0.37, -0.17]	small
4	occupation	apprentice vs. student	147	47	89.13	106.49	0.66	5.4e-02	n/c	n/c
5	occupation	apprentice vs. fulltime	147	4898	89.13	85.94	0.46	2.0e+00	n/c	n/c
6	occupation	halftime vs. student	1382	47	96.08	106.49	0.55	5.6e+00	n/c	n/c
7	place of residence	rural vs. urban	1708	3376	86.60	88.64	0.54	2e-04***	[-0.11, -0.05]	negligible
8	place of residence	city vs. rural	1390	1708	89.67	86.60	0.44	3e-04***	[0.09, 0.17]	small
9	place of residence	city vs. urban	1390	3376	89.67	88.64	0.47	5e-03**	[0.02, 0.09]	negligible
10	season	fall vs. summer	1793	1336	89.01	87.31	0.48	6.5e-01	n/c	n/c
11	season	fall vs. winter	1793	1940	89.01	88.08	0.48	6.6e-01	n/c	n/c
12	season	summer vs. winter	1336	1940	87.31	88.08	0.50	9.3e-01	n/c	n/c
13	season	fall vs. spring	1793	1405	89.01	88.74	0.49	1.1e+00	n/c	n/c
14	season	spring vs. winter	1405	1940	88.74	88.08	0.50	1.4e+00	n/c	n/c
15	season	spring vs. summer	1405	1336	88.74	87.31	0.50	2.0e+00	n/c	n/c
16	weekday	sunday vs. workday	111	6117	112.06	87.63	0.36	1.2e-03**	[0.13, 0.42]	small
17	weekday	saturday vs. sunday	246	111	94.80	112.06	0.61	8.0e-03**	[-0.34, -0.07]	small
18	weekday	saturday vs. workday	246	6117	94.80	87.63	0.47	1.5e-01	n/c	n/c

Significance codes: $0.0 <$ p*** $\leq 0.001 <$ p** $\leq 0.01 <$ p* ≤ 0.05
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Note: it is assumed that H-W or W-H trips are only
executed by the following occupation types: fulltime, halftime, apprentice, student

Table 55: Trip level (Cliff's method): main effects on departure time [5min] (first trips per day except H-W trips)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	number of trips per day	5to6 vs. 7to17	1936	1134	115.69	106.90	0.40	1.0e-04***	[0.16, 0.25]	small
2	number of trips per day	3to4 vs. 7to17	4318	1134	128.06	106.90	0.31	2.0e-04***	[0.36, 0.42]	medium
3	number of trips per day	3to4 vs. 5to6	4318	1936	128.06	115.69	0.40	3.0e-04***	[0.17, 0.23]	small
4	number of trips per day	1to2 vs. 7to17	4976	1134	148.57	106.90	0.20	4.0e-04***	[0.57, 0.62]	large
5	number of trips per day	1to2 vs. 5to6	4976	1936	148.57	115.69	0.28	5.0e-04***	[0.42, 0.47]	medium
6	number of trips per day	1to2 vs. 3to4	4976	4318	148.57	128.06	0.37	6.0e-04***	[0.24, 0.29]	small
7	number of trips per day	5to6 vs. 7to17	1936	1134	115.69	106.90	0.40	7.0e-04***	[0.16, 0.25]	small
8	number of trips per day	3to4 vs. 7to17	4318	1134	128.06	106.90	0.31	8.0e-04***	[0.36, 0.42]	medium
9	number of trips per day	3to4 vs. 5to6	4318	1936	128.06	115.69	0.40	9.0e-04***	[0.17, 0.23]	small
10	number of trips per day	1to2 vs. 7to17	4976	1134	148.57	106.90	0.20	1.0e-03***	[0.57, 0.62]	large
11	number of trips per day	1to2 vs. 5to6	4976	1936	148.57	115.69	0.28	1.1e-03**	[0.42, 0.47]	medium
12	number of trips per day	1to2 vs. 3to4	4976	4318	148.57	128.06	0.37	1.2e-03**	[0.24, 0.29]	small
13	place of residence	city vs. urban	3081	6158	135.06	132.32	0.47	2e-04***	[0.03, 0.08]	negligible
14	place of residence	city vs. rural	3081	3125	135.06	130.08	0.46	3e-04***	[0.06, 0.12]	negligible
15	place of residence	rural vs. urban	3125	6158	130.08	132.32	0.52	3e-03**	[-0.06, -0.01]	negligible
16	season	spring vs. winter	2728	3692	130.92	132.73	0.52	1.1e-01	n/c	n/c
17	season	spring vs. summer	2728	2548	130.92	133.72	0.52	2.9e-01	n/c	n/c
18	season	fall vs. summer	3396	2548	132.38	133.72	0.51	7.0e-01	n/c	n/c
19	season	summer vs. winter	2548	3692	133.72	132.73	0.50	8.3e-01	n/c	n/c
20	season	fall vs. winter	3396	3692	132.38	132.73	0.51	8.4e-01	n/c	n/c
21	season	fall vs. spring	3396	2728	132.38	130.92	0.49	8.4e-01	n/c	n/c
22	trip purpose	leisure vs. shopping	3257	4139	146.70	132.73	0.41	8.0e-04***	[0.16, 0.21]	small
23	trip purpose	errand vs. shopping	2547	4139	129.45	132.73	0.54	9.0e-04***	[-0.12, -0.06]	negligible
24	trip purpose	errand vs. leisure	2547	3257	129.45	146.70	0.62	1.0e-03***	[-0.27, -0.22]	small
25	trip purpose	education vs. shopping	359	4139	93.71	132.73	0.89	1.1e-03**	[-0.83, -0.74]	large
26	trip purpose	education vs. leisure	359	3257	93.71	146.70	0.89	1.2e-03**	[-0.81, -0.74]	large
27	trip purpose	education vs. errand	359	2547	93.71	129.45	0.87	1.3e-03**	[-0.77, -0.69]	large
28	trip purpose	business vs. shopping	270	4139	110.33	132.73	0.72	1.4e-03**	[-0.51, -0.37]	medium
29	trip purpose	business vs. leisure	270	3257	110.33	146.70	0.76	1.5e-03**	[-0.58, -0.45]	large
30	trip purpose	business vs. errand	270	2547	110.33	129.45	0.68	1.6e-03**	[-0.44, -0.29]	medium
31	trip purpose	business vs. education	270	359	110.33	93.71	0.32	1.7e-03**	[0.27, 0.45]	medium
32	trip purpose	accompanying vs. shopping	1791	4139	121.18	132.73	0.65	1.8e-03**	[-0.34, -0.27]	medium
33	trip purpose	accompanying vs. leisure	1791	3257	121.18	146.70	0.69	1.9e-03**	[-0.42, -0.35]	medium
34	trip purpose	accompanying vs. errand	1791	2547	121.18	129.45	0.62	2.0e-03**	[-0.27, -0.20]	small
35	trip purpose	accompanying vs. education	1791	359	121.18	93.71	0.27	2.1e-03**	[0.42, 0.52]	medium
36	trip purpose	accompanying vs. business	1791	270	121.18	110.33	0.45	2.8e-02*	[0.03, 0.18]	small
37	weekday	sunday vs. workday	1571	8647	142.65	130.58	0.38	1e-04***	[0.20, 0.26]	small
38	weekday	saturday vs. workday	2146	8647	132.47	130.58	0.45	2e-04***	[0.07, 0.12]	negligible
39	weekday	saturday vs. sunday	2146	1571	132.47	142.65	0.59	3e-04***	[-0.21, -0.14]	small

Significance codes: 0.0 < p*** ≤ 0.001 < p** ≤ 0.01 < p* ≤ 0.05
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Note: it is assumed that H-W or W-H trips are only
executed by the following occupation types: fulltime, halftime, apprentice, student

Table 56: Trip level (Cliff's method): main effects on driving time [5min] (H-W or W-H trips)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	occupation	fulltime vs. halftime	10207	3065	5.37	3.96	0.38	2.1e-03**	[0.21, 0.25]	small
2	occupation	apprentice vs. fulltime	339	10207	4.62	5.37	0.56	4.0e-03**	[-0.17, -0.05]	small
3	occupation	apprentice vs. halftime	339	3065	4.62	3.96	0.44	9.5e-03**	[0.05, 0.18]	small
4	occupation	halftime vs. student	3065	106	3.96	4.69	0.58	1.6e-01	n/c	n/c
5	occupation	fulltime vs. student	10207	106	5.37	4.69	0.46	2.5e+00	n/c	n/c
6	occupation	apprentice vs. student	339	106	4.62	4.69	0.52	9.8e+00	n/c	n/c
7	place of residence	city vs. urban	2820	7158	5.30	4.92	0.46	2e-04***	[0.06, 0.10]	negligible
8	place of residence	city vs. rural	2820	3739	5.30	5.04	0.44	3e-04***	[0.09, 0.14]	small
9	place of residence	rural vs. urban	3739	7158	5.04	4.92	0.52	5e-03**	[-0.06, -0.01]	negligible
10	season	spring vs. winter	2997	4078	4.94	5.15	0.52	3.6e-03**	[-0.07, -0.02]	negligible
11	season	fall vs. winter	3796	4078	4.88	5.15	0.52	2.0e-02*	[-0.06, -0.01]	negligible
12	season	spring vs. summer	2997	2846	4.94	5.15	0.51	2.4e-01	n/c	n/c
13	season	fall vs. summer	3796	2846	4.88	5.15	0.51	4.2e-01	n/c	n/c
14	season	fall vs. spring	3796	2997	4.88	4.94	0.49	4.5e-01	n/c	n/c
15	season	summer vs. winter	2846	4078	5.15	5.15	0.51	5.7e-01	n/c	n/c
16	weekday	sunday vs. workday	294	12872	4.84	5.07	0.61	2.0e-04***	[-0.29, -0.16]	small
17	weekday	saturday vs. workday	551	12872	4.18	5.07	0.58	3.0e-04***	[-0.20, -0.11]	small
18	weekday	saturday vs. sunday	551	294	4.18	4.84	0.46	4.3e-02*	[0.00, 0.17]	negligible

Significance codes: 0.0 < p*** ≤ 0.001 < p** ≤ 0.01 < p* ≤ 0.05
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Note: it is assumed that H-W or W-H trips are only
executed by the following occupation types: fulltime, halftime, apprentice, student

Table 57: Trip level (Cliff's method): interaction effects on driving time [5min] controlling for place of residence = city (all trips except H-W or W-H trips)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	number of trips per day	5to6 vs. 7to17	3040	2341	3.53	3.10	0.46	1e-04***	[0.05, 0.11]	negligible
2	number of trips per day	3to4 vs. 7to17	4801	2341	3.97	3.10	0.43	2e-04***	[0.11, 0.17]	small
3	number of trips per day	3to4 vs. 5to6	4801	3040	3.97	3.53	0.47	3e-04***	[0.03, 0.09]	negligible
4	number of trips per day	1to2 vs. 7to17	2780	2341	6.14	3.10	0.35	4e-04***	[0.28, 0.33]	medium
5	number of trips per day	1to2 vs. 5to6	2780	3040	6.14	3.53	0.38	5e-04***	[0.20, 0.26]	small
6	number of trips per day	1to2 vs. 3to4	2780	4801	6.14	3.97	0.41	6e-04***	[0.15, 0.20]	small
7	season	summer vs. winter	2258	4292	4.29	4.05	0.49	4.6e-01	n/c	n/c
8	season	spring vs. summer	2707	2258	4.23	4.29	0.51	5.3e-01	n/c	n/c
9	season	fall vs. summer	3705	2258	4.23	4.29	0.51	6.4e-01	n/c	n/c
10	season	spring vs. winter	2707	4292	4.23	4.05	0.50	8.2e-01	n/c	n/c
11	season	fall vs. winter	3705	4292	4.23	4.05	0.50	1.6e+00	n/c	n/c
12	season	fall vs. spring	3705	2707	4.23	4.23	0.50	2.1e+00	n/c	n/c
13	trip distance category	outside city vs. unknown	2762	1157	6.86	5.96	0.40	1e-04***	[0.16, 0.24]	small
14	trip distance category	inside city vs. unknown	8786	1157	3.07	5.96	0.63	2e-04***	[-0.30, -0.23]	small
15	trip distance category	inside city vs. outside city	8786	2762	3.07	6.86	0.74	3e-04***	[-0.51, -0.47]	medium
16	trip purpose	leisure vs. shopping	3990	4331	5.48	3.03	0.33	9.0e-04***	[0.31, 0.36]	medium
17	trip purpose	errand vs. shopping	2210	4331	4.04	3.03	0.39	1.0e-03***	[0.19, 0.24]	small
18	trip purpose	errand vs. leisure	2210	3990	4.04	5.48	0.57	1.1e-03**	[-0.16, -0.10]	small
19	trip purpose	education vs. shopping	155	4331	5.77	3.03	0.27	1.2e-03**	[0.39, 0.54]	medium
20	trip purpose	education vs. errand	155	2210	5.77	4.04	0.37	1.3e-03**	[0.18, 0.36]	small
21	trip purpose	business vs. shopping	339	4331	9.17	3.03	0.27	1.4e-03**	[0.41, 0.53]	medium
22	trip purpose	business vs. leisure	339	3990	9.17	5.48	0.41	1.5e-03**	[0.11, 0.24]	small
23	trip purpose	business vs. errand	339	2210	9.17	4.04	0.35	1.6e-03**	[0.23, 0.36]	small
24	trip purpose	accompanying vs. shopping	1931	4331	3.21	3.03	0.47	1.7e-03**	[0.03, 0.10]	negligible
25	trip purpose	accompanying vs. leisure	1931	3990	3.21	5.48	0.64	1.8e-03**	[-0.31, -0.25]	small
26	trip purpose	accompanying vs. errand	1931	2210	3.21	4.04	0.58	1.9e-03**	[-0.19, -0.12]	small
27	trip purpose	accompanying vs. education	1931	155	3.21	5.77	0.71	2.0e-03**	[-0.49, -0.33]	medium
28	trip purpose	accompanying vs. business	1931	339	3.21	9.17	0.71	2.1e-03**	[-0.48, -0.35]	medium
29	trip purpose	education vs. leisure	155	3990	5.77	5.48	0.43	3.2e-02*	[0.05, 0.22]	small
30	trip purpose	business vs. education	339	155	9.17	5.77	0.47	2.1e+00	n/c	n/c
31	weekday	sunday vs. workday	1206	9800	5.75	3.92	0.44	2e-04***	[0.09, 0.16]	small
32	weekday	saturday vs. sunday	1956	1206	4.51	5.75	0.54	3e-04***	[-0.13, -0.04]	negligible
33	weekday	saturday vs. workday	1956	9800	4.51	3.92	0.48	2e-03**	[0.02, 0.07]	negligible

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Note: it is assumed that H-W or W-H trips are only
executed by the following occupation types: fulltime, halftime, apprentice, student

Table 58: Trip level (Cliff's method): interaction effects on driving time [5min] controlling for place of residence = rural (all trips except H-W or W-H trips)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	number of trips per day	5to6 vs. 7to17	3372	2705	3.17	2.55	0.42	1e-04***	[0.13, 0.18]	small
2	number of trips per day	3to4 vs. 7to17	4765	2705	3.82	2.55	0.38	2e-04***	[0.22, 0.27]	small
3	number of trips per day	3to4 vs. 5to6	4765	3372	3.82	3.17	0.45	3e-04***	[0.07, 0.12]	negligible
4	number of trips per day	1to2 vs. 7to17	2771	2705	5.93	2.55	0.31	4e-04***	[0.35, 0.40]	medium
5	number of trips per day	1to2 vs. 5to6	2771	3372	5.93	3.17	0.38	5e-04***	[0.21, 0.27]	small
6	number of trips per day	1to2 vs. 3to4	2771	4765	5.93	3.82	0.42	6e-04***	[0.13, 0.18]	small
7	season	spring vs. summer	3786	2895	3.70	4.06	0.52	4.2e-03**	[-0.07, -0.02]	negligible
8	season	fall vs. spring	3405	3786	4.03	3.70	0.48	2.5e-02*	[0.01, 0.06]	negligible
9	season	spring vs. winter	3786	3527	3.70	3.61	0.51	2.8e-01	n/c	n/c
10	season	summer vs. winter	2895	3527	4.06	3.61	0.49	2.9e-01	n/c	n/c
11	season	fall vs. summer	3405	2895	4.03	4.06	0.50	5.5e-01	n/c	n/c
12	season	fall vs. winter	3405	3527	4.03	3.61	0.49	5.6e-01	n/c	n/c
13	trip distance category	outside city vs. unknown	6071	1453	5.17	4.43	0.41	1e-04***	[0.14, 0.21]	small
14	trip distance category	inside city vs. unknown	5816	1453	2.23	4.43	0.67	2e-04***	[-0.38, -0.31]	medium
15	trip distance category	inside city vs. outside city	5816	6071	2.23	5.17	0.78	3e-04***	[-0.57, -0.54]	large
16	trip purpose	leisure vs. shopping	4038	4394	4.96	2.90	0.38	9.0e-04***	[0.21, 0.26]	small
17	trip purpose	errand vs. shopping	2522	4394	3.66	2.90	0.43	1.0e-03***	[0.12, 0.18]	small
18	trip purpose	errand vs. leisure	2522	4038	3.66	4.96	0.55	1.1e-03**	[-0.12, -0.07]	negligible
19	trip purpose	education vs. shopping	215	4394	6.06	2.90	0.22	1.2e-03**	[0.50, 0.62]	large
20	trip purpose	education vs. leisure	215	4038	6.06	4.96	0.34	1.3e-03**	[0.26, 0.39]	medium
21	trip purpose	education vs. errand	215	2522	6.06	3.66	0.28	1.4e-03**	[0.37, 0.50]	medium
22	trip purpose	business vs. shopping	315	4394	9.32	2.90	0.26	1.5e-03**	[0.41, 0.53]	medium
23	trip purpose	business vs. leisure	315	4038	9.32	4.96	0.37	1.6e-03**	[0.19, 0.33]	small
24	trip purpose	business vs. errand	315	2522	9.32	3.66	0.32	1.7e-03**	[0.29, 0.42]	medium
25	trip purpose	accompanying vs. leisure	2129	4038	2.80	4.96	0.63	1.8e-03**	[-0.28, -0.23]	small
26	trip purpose	accompanying vs. errand	2129	2522	2.80	3.66	0.59	1.9e-03**	[-0.20, -0.14]	small
27	trip purpose	accompanying vs. education	2129	215	2.80	6.06	0.79	2.0e-03**	[-0.64, -0.51]	large
28	trip purpose	accompanying vs. business	2129	315	2.80	9.32	0.74	2.1e-03**	[-0.55, -0.42]	medium
29	trip purpose	accompanying vs. shopping	2129	4394	2.80	2.90	0.51	9.6e-01	n/c	n/c
30	trip purpose	business vs. education	315	215	9.32	6.06	0.51	4.8e+00	n/c	n/c
31	weekday	sunday vs. workday	1225	10280	5.40	3.61	0.42	2.0e-04***	[0.12, 0.19]	small
32	weekday	saturday vs. sunday	2108	1225	4.04	5.40	0.56	3.0e-04***	[-0.17, -0.09]	small
33	weekday	saturday vs. workday	2108	10280	4.04	3.61	0.49	5.1e-02	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Note: it is assumed that H-W or W-H trips are only
executed by the following occupation types: fulltime, halftime, apprentice, student

Table 59: Trip level (Cliff's method): interaction effects on driving time [5min] controlling for place of residence = urban (all trips except H-W or W-H trips)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	number of trips per day	5to6 vs. 7to17	6775	5913	3.10	2.58	0.45	1e-04***	[0.08, 0.12]	negligible
2	number of trips per day	3to4 vs. 7to17	9205	5913	3.71	2.58	0.40	2e-04***	[0.17, 0.21]	small
3	number of trips per day	3to4 vs. 5to6	9205	6775	3.71	3.10	0.45	3e-04***	[0.08, 0.11]	negligible
4	number of trips per day	1to2 vs. 7to17	5558	5913	5.35	2.58	0.34	4e-04***	[0.30, 0.34]	medium
5	number of trips per day	1to2 vs. 5to6	5558	6775	5.35	3.10	0.39	5e-04***	[0.21, 0.25]	small
6	number of trips per day	1to2 vs. 3to4	5558	9205	5.35	3.71	0.43	6e-04***	[0.12, 0.15]	small
7	season	spring vs. summer	5737	5817	3.59	3.80	0.53	6.0e-04***	[-0.07, -0.03]	negligible
8	season	fall vs. summer	7663	5817	3.69	3.80	0.52	1.0e-03***	[-0.06, -0.02]	negligible
9	season	summer vs. winter	5817	8234	3.80	3.55	0.49	2.4e-02*	[0.01, 0.05]	negligible
10	season	spring vs. winter	5737	8234	3.59	3.55	0.51	3.9e-02*	[-0.04, -0.01]	negligible
11	season	fall vs. winter	7663	8234	3.69	3.55	0.51	2.2e-01	n/c	n/c
12	season	fall vs. spring	7663	5737	3.69	3.59	0.49	3.4e-01	n/c	n/c
13	trip distance category	outside city vs. unknown	11517	3012	5.08	4.65	0.43	1e-04***	[0.12, 0.17]	small
14	trip distance category	inside city vs. unknown	12336	3012	2.03	4.65	0.72	2e-04***	[-0.46, -0.41]	medium
15	trip distance category	inside city vs. outside city	12336	11517	2.03	5.08	0.80	3e-04***	[-0.61, -0.59]	large
16	trip purpose	leisure vs. shopping	7914	9047	4.76	2.80	0.37	8.0e-04***	[0.24, 0.28]	small
17	trip purpose	errand vs. shopping	4991	9047	3.46	2.80	0.44	9.0e-04***	[0.10, 0.14]	small
18	trip purpose	errand vs. leisure	4991	7914	3.46	4.76	0.57	1.0e-03***	[-0.16, -0.12]	small
19	trip purpose	education vs. shopping	456	9047	5.87	2.80	0.21	1.1e-03**	[0.54, 0.62]	large
20	trip purpose	education vs. leisure	456	7914	5.87	4.76	0.33	1.2e-03**	[0.29, 0.39]	medium
21	trip purpose	education vs. errand	456	4991	5.87	3.46	0.26	1.3e-03**	[0.43, 0.52]	medium
22	trip purpose	business vs. shopping	673	9047	7.17	2.80	0.30	1.4e-03**	[0.35, 0.44]	medium
23	trip purpose	business vs. leisure	673	7914	7.17	4.76	0.42	1.5e-03**	[0.11, 0.20]	small
24	trip purpose	business vs. errand	673	4991	7.17	3.46	0.36	1.6e-03**	[0.24, 0.33]	small
25	trip purpose	business vs. education	673	456	7.17	5.87	0.58	1.7e-03**	[-0.22, -0.09]	small
26	trip purpose	accompanying vs. leisure	4368	7914	2.83	4.76	0.62	1.8e-03**	[-0.26, -0.22]	small
27	trip purpose	accompanying vs. errand	4368	4991	2.83	3.46	0.55	1.9e-03**	[-0.12, -0.08]	small
28	trip purpose	accompanying vs. education	4368	456	2.83	5.87	0.78	2.0e-03**	[-0.61, -0.52]	large
29	trip purpose	accompanying vs. business	4368	673	2.83	7.17	0.69	2.1e-03**	[-0.42, -0.33]	medium
30	trip purpose	accompanying vs. shopping	4368	9047	2.83	2.80	0.49	6.4e-01	n/c	n/c
31	weekday	sunday vs. workday	2420	20890	4.97	3.46	0.43	2.0e-04***	[0.11, 0.16]	small
32	weekday	saturday vs. sunday	4141	2420	3.84	4.97	0.56	3.0e-04***	[-0.15, -0.09]	small
33	weekday	saturday vs. workday	4141	20890	3.84	3.46	0.50	6.3e-01	n/c	n/c

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Note: it is assumed that H-W or W-H trips are only
executed by the following occupation types: fulltime, halftime, apprentice, student

Table 60: Trip level (Cliff's method): main effects on parking time [5min] (H-W trips)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	occupation	fulltime vs. student	5404	57	93.68	71.04	0.32	1.9e-03**	[0.20, 0.49]	medium
2	occupation	fulltime vs. halftime	5404	1655	93.68	65.06	0.24	2.0e-03**	[0.49, 0.54]	large
3	occupation	apprentice vs. halftime	169	1655	87.63	65.06	0.29	2.1e-03**	[0.33, 0.51]	medium
4	occupation	apprentice vs. fulltime	169	5404	87.63	93.68	0.58	3.6e-03**	[-0.24, -0.08]	small
5	occupation	apprentice vs. student	169	57	87.63	71.04	0.37	1.0e-01	n/c	n/c
6	occupation	halftime vs. student	1655	57	65.06	71.04	0.55	4.6e+00	n/c	n/c
7	weekday	sunday vs. workday	133	6872	70.71	87.72	0.64	2.0e-04***	[-0.37, -0.17]	small
8	weekday	saturday vs. workday	280	6872	73.51	87.72	0.63	3.0e-04***	[-0.33, -0.20]	small
9	weekday	saturday vs. sunday	280	133	73.51	70.71	0.48	5.5e-01	n/c	n/c

Significance codes: $0.0 <$ p*** $\leq 0.001 <$ p** $\leq 0.01 <$ p* ≤ 0.05
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Note: it is assumed that H-W or W-H trips are only
executed by the following occupation types: fulltime, halftime, apprentice, student

Table 61: Trip level (Cliff's method): interaction effects on parking time [5min] controlling for place of residence = city (all trips except H-W trips)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	number of trips per day	5to6 vs. 7to17	3061	2349	17.66	12.86	0.42	2e-04***	[0.12, 0.19]	small
2	number of trips per day	3to4 vs. 7to17	4837	2349	20.50	12.86	0.40	3e-04***	[0.17, 0.23]	small
3	number of trips per day	1to2 vs. 7to17	2815	2349	28.22	12.86	0.30	4e-04***	[0.36, 0.43]	medium
4	number of trips per day	1to2 vs. 5to6	2815	3061	28.22	17.66	0.38	5e-04***	[0.21, 0.28]	small
5	number of trips per day	1to2 vs. 3to4	2815	4837	28.22	20.50	0.40	6e-04***	[0.16, 0.24]	small
6	number of trips per day	3to4 vs. 5to6	4837	3061	20.50	17.66	0.48	3e-03**	[0.02, 0.08]	negligible
7	season	summer vs. winter	2271	4331	19.86	17.68	0.46	5.0e-04***	[0.04, 0.11]	negligible
8	season	fall vs. winter	3732	4331	19.75	17.68	0.47	6.0e-04***	[0.03, 0.09]	negligible
9	season	spring vs. winter	2728	4331	19.60	17.68	0.48	2.4e-02*	[0.01, 0.08]	negligible
10	season	spring vs. summer	2728	2271	19.60	19.86	0.52	3.3e-01	n/c	n/c
11	season	fall vs. summer	3732	2271	19.75	19.86	0.51	4.3e-01	n/c	n/c
12	season	fall vs. spring	3732	2728	19.75	19.60	0.49	6.8e-01	n/c	n/c
13	trip purpose	leisure vs. shopping	4025	4354	28.32	14.50	0.28	8.0e-04***	[0.42, 0.47]	medium
14	trip purpose	errand vs. shopping	2223	4354	18.12	14.50	0.45	9.0e-04***	[0.06, 0.13]	negligible
15	trip purpose	errand vs. leisure	2223	4025	18.12	28.32	0.66	1.0e-03***	[-0.36, -0.29]	medium
16	trip purpose	education vs. shopping	156	4354	47.56	14.50	0.20	1.1e-03**	[0.50, 0.69]	large
17	trip purpose	education vs. leisure	156	4025	47.56	28.32	0.35	1.2e-03**	[0.18, 0.42]	medium
18	trip purpose	education vs. errand	156	2223	47.56	18.12	0.24	1.3e-03**	[0.42, 0.61]	large
19	trip purpose	business vs. shopping	360	4354	27.78	14.50	0.34	1.4e-03**	[0.24, 0.39]	medium
20	trip purpose	business vs. errand	360	2223	27.78	18.12	0.39	1.5e-03**	[0.15, 0.30]	small
21	trip purpose	business vs. education	360	156	27.78	47.56	0.67	1.6e-03**	[-0.45, -0.21]	medium
22	trip purpose	accompanying vs. shopping	1938	4354	11.01	14.50	0.68	1.7e-03**	[-0.40, -0.33]	medium
23	trip purpose	accompanying vs. leisure	1938	4025	11.01	28.32	0.81	1.8e-03**	[-0.64, -0.58]	large
24	trip purpose	accompanying vs. errand	1938	2223	11.01	18.12	0.70	1.9e-03**	[-0.44, -0.36]	medium
25	trip purpose	accompanying vs. education	1938	156	11.01	47.56	0.85	2.0e-03**	[-0.77, -0.62]	large
26	trip purpose	accompanying vs. business	1938	360	11.01	27.78	0.77	2.1e-03**	[-0.59, -0.48]	large
27	trip purpose	business vs. leisure	360	4025	27.78	28.32	0.54	2.9e-01	n/c	n/c
28	weekday	saturday vs. workday	1961	9893	21.11	17.88	0.47	2e-04***	[0.03, 0.10]	negligible
29	weekday	sunday vs. workday	1208	9893	26.34	17.88	0.42	3e-04***	[0.12, 0.21]	small
30	weekday	saturday vs. sunday	1961	1208	21.11	26.34	0.55	4e-04***	[-0.16, -0.05]	small

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Note: it is assumed that H-W or W-H trips are only
executed by the following occupation types: fulltime, halftime, apprentice, student

Table 62: Trip level (Cliff's method): interaction effects on parking time [5min] controlling for place of residence = rural (all trips except H-W trips)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	number of trips per day	5to6 vs. 7to17	3398	2717	17.51	13.84	0.44	1e-04***	[0.09, 0.15]	small
2	number of trips per day	3to4 vs. 7to17	4809	2717	22.19	13.84	0.39	2e-04***	[0.19, 0.25]	small
3	number of trips per day	3to4 vs. 5to6	4809	3398	22.19	17.51	0.45	3e-04***	[0.08, 0.14]	small
4	number of trips per day	1to2 vs. 7to17	2815	2717	27.72	13.84	0.32	4e-04***	[0.32, 0.39]	medium
5	number of trips per day	1to2 vs. 5to6	2815	3398	27.72	17.51	0.38	5e-04***	[0.20, 0.28]	small
6	number of trips per day	1to2 vs. 3to4	2815	4809	27.72	22.19	0.43	6e-04***	[0.10, 0.17]	small
7	season	fall vs. winter	3435	3554	19.20	19.46	0.50	7.5e-01	n/c	n/c
8	season	spring vs. summer	3829	2921	19.35	20.15	0.51	1.3e+00	n/c	n/c
9	season	spring vs. winter	3829	3554	19.35	19.46	0.50	1.4e+00	n/c	n/c
10	season	fall vs. summer	3435	2921	19.20	20.15	0.50	1.8e+00	n/c	n/c
11	season	fall vs. spring	3435	3829	19.20	19.35	0.49	1.8e+00	n/c	n/c
12	season	summer vs. winter	2921	3554	20.15	19.46	0.49	2.1e+00	n/c	n/c
13	trip purpose	leisure vs. shopping	4078	4419	28.65	14.96	0.28	8.0e-04***	[0.41, 0.46]	medium
14	trip purpose	errand vs. shopping	2542	4419	17.95	14.96	0.44	9.0e-04***	[0.09, 0.15]	small
15	trip purpose	errand vs. leisure	2542	4078	17.95	28.65	0.66	1.0e-03***	[-0.36, -0.29]	medium
16	trip purpose	education vs. shopping	218	4419	54.76	14.96	0.18	1.1e-03**	[0.56, 0.72]	large
17	trip purpose	education vs. leisure	218	4078	54.76	28.65	0.29	1.2e-03**	[0.31, 0.51]	medium
18	trip purpose	education vs. errand	218	2542	54.76	17.95	0.20	1.3e-03**	[0.51, 0.67]	large
19	trip purpose	business vs. shopping	338	4419	31.11	14.96	0.33	1.4e-03**	[0.25, 0.41]	medium
20	trip purpose	business vs. errand	338	2542	31.11	17.95	0.38	1.5e-03**	[0.15, 0.32]	small
21	trip purpose	business vs. education	338	218	31.11	54.76	0.69	1.6e-03**	[-0.48, -0.27]	medium
22	trip purpose	accompanying vs. shopping	2144	4419	11.45	14.96	0.66	1.7e-03**	[-0.36, -0.29]	medium
23	trip purpose	accompanying vs. leisure	2144	4078	11.45	28.65	0.79	1.8e-03**	[-0.62, -0.56]	large
24	trip purpose	accompanying vs. errand	2144	2542	11.45	17.95	0.69	1.9e-03**	[-0.42, -0.35]	medium
25	trip purpose	accompanying vs. education	2144	218	11.45	54.76	0.87	2.0e-03**	[-0.79, -0.68]	large
26	trip purpose	accompanying vs. business	2144	338	11.45	31.11	0.76	2.1e-03**	[-0.58, -0.47]	large
27	trip purpose	business vs. leisure	338	4078	31.11	28.65	0.52	2.7e+00	n/c	n/c
28	weekday	sunday vs. workday	1232	10392	26.80	17.91	0.39	2e-04***	[0.17, 0.26]	small
29	weekday	saturday vs. workday	2115	10392	23.82	17.91	0.44	3e-04***	[0.09, 0.15]	small
30	weekday	saturday vs. sunday	2115	1232	23.82	26.80	0.54	7e-04***	[-0.14, -0.04]	negligible

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Note: it is assumed that H-W or W-H trips are only
executed by the following occupation types: fulltime, halftime, apprentice, student

Table 63: Trip level (Cliff's method): interaction effects on parking time [5min] controlling for place of residence = urban (all trips except H-W trips)

	Factor	$Level_1$ vs. $level_2$	n_1	n_2	$mean_1$	$mean_2$	P-statistic	$p_{adj.}$	CI Cliff's δ	Effect size
1	number of trips per day	5to6 vs. 7to17	6817	5937	17.28	12.71	0.43	1e-04***	[0.12, 0.16]	small
2	number of trips per day	3to4 vs. 7to17	9290	5937	21.29	12.71	0.38	2e-04***	[0.21, 0.25]	small
3	number of trips per day	3to4 vs. 5to6	9290	6817	21.29	17.28	0.45	3e-04***	[0.07, 0.12]	negligible
4	number of trips per day	1to2 vs. 7to17	5634	5937	27.60	12.71	0.32	4e-04***	[0.33, 0.38]	medium
5	number of trips per day	1to2 vs. 5to6	5634	6817	27.60	17.28	0.39	5e-04***	[0.19, 0.24]	small
6	number of trips per day	1to2 vs. 3to4	5634	9290	27.60	21.29	0.44	6e-04***	[0.10, 0.15]	small
7	season	fall vs. summer	7742	5853	18.54	19.56	0.51	2.5e-01	n/c	n/c
8	season	summer vs. winter	5853	8309	19.56	18.36	0.49	3.0e-01	n/c	n/c
9	season	spring vs. summer	5774	5853	18.54	19.56	0.51	5.6e-01	n/c	n/c
10	season	fall vs. winter	7742	8309	18.54	18.36	0.50	8.3e-01	n/c	n/c
11	season	spring vs. winter	5774	8309	18.54	18.36	0.50	1.6e+00	n/c	n/c
12	season	fall vs. spring	7742	5774	18.54	18.54	0.50	2.0e+00	n/c	n/c
13	trip purpose	leisure vs. shopping	7997	9088	26.87	14.70	0.29	8.0e-04***	[0.41, 0.44]	medium
14	trip purpose	errand vs. shopping	5019	9088	17.70	14.70	0.45	9.0e-04***	[0.07, 0.12]	negligible
15	trip purpose	errand vs. leisure	5019	7997	17.70	26.87	0.66	1.0e-03***	[-0.34, -0.30]	medium
16	trip purpose	education vs. shopping	461	9088	54.24	14.70	0.17	1.1e-03**	[0.60, 0.71]	large
17	trip purpose	education vs. leisure	461	7997	54.24	26.87	0.28	1.2e-03**	[0.37, 0.51]	medium
18	trip purpose	education vs. errand	461	5019	54.24	17.70	0.20	1.3e-03**	[0.55, 0.66]	large
19	trip purpose	business vs. shopping	724	9088	30.76	14.70	0.32	1.4e-03**	[0.30, 0.40]	medium
20	trip purpose	business vs. errand	724	5019	30.76	17.70	0.37	1.5e-03**	[0.21, 0.31]	small
21	trip purpose	business vs. education	724	461	30.76	54.24	0.70	1.6e-03**	[-0.46, -0.32]	medium
22	trip purpose	accompanying vs. shopping	4387	9088	10.55	14.70	0.67	1.7e-03**	[-0.37, -0.32]	medium
23	trip purpose	accompanying vs. leisure	4387	7997	10.55	26.87	0.80	1.8e-03**	[-0.62, -0.58]	large
24	trip purpose	accompanying vs. errand	4387	5019	10.55	17.70	0.69	1.9e-03**	[-0.40, -0.36]	medium
25	trip purpose	accompanying vs. education	4387	461	10.55	54.24	0.88	2.0e-03**	[-0.79, -0.72]	large
26	trip purpose	accompanying vs. business	4387	724	10.55	30.76	0.78	2.1e-03**	[-0.59, -0.51]	large
27	trip purpose	business vs. leisure	724	7997	30.76	26.87	0.52	1.8e+00	n/c	n/c
28	weekday	sunday vs. workday	2427	21099	24.41	17.88	0.41	2e-04***	[0.15, 0.21]	small
29	weekday	saturday vs. sunday	4152	2427	19.97	24.41	0.57	3e-04***	[-0.17, -0.10]	small
30	weekday	saturday vs. workday	4152	21099	19.97	17.88	0.48	3e-04***	[0.02, 0.07]	negligible

Significance codes: $0.0 < p^{***} \leq 0.001 < p^{**} \leq 0.01 < p^{*} \leq 0.05$
Family-wise error rate correction method: Holm–Bonferroni
n/c: not calculated as p-value is not significant
n/a: not available as $min(n_1, n_2) \leq 1$

$\alpha_{CI} = 0.05$
Effect size: negligible: $0.0 \leq |\overline{CI}| < 0.1$
small: $0.1 \leq |\overline{CI}| < 0.3$
medium: $0.3 \leq |\overline{CI}| < 0.5$
large: $0.5 \leq |\overline{CI}| \leq 1$

Note: it is assumed that H-W or W-H trips are only
executed by the following occupation types: fulltime, halftime, apprentice, student

A.5 Additional χ^2-test results and mosaic plots

A.5.1 Household level

Additional research questions and corresponding results for possible interaction effects:

HL-C1-1: Is the household type dependent on the household's economic status?

H_0: *The attribute 'economic household status' is* independent *from the attribute 'place of residence'.*

H_1: *The attribute 'economic household status' is* dependent *on the attribute 'place of residence'.*

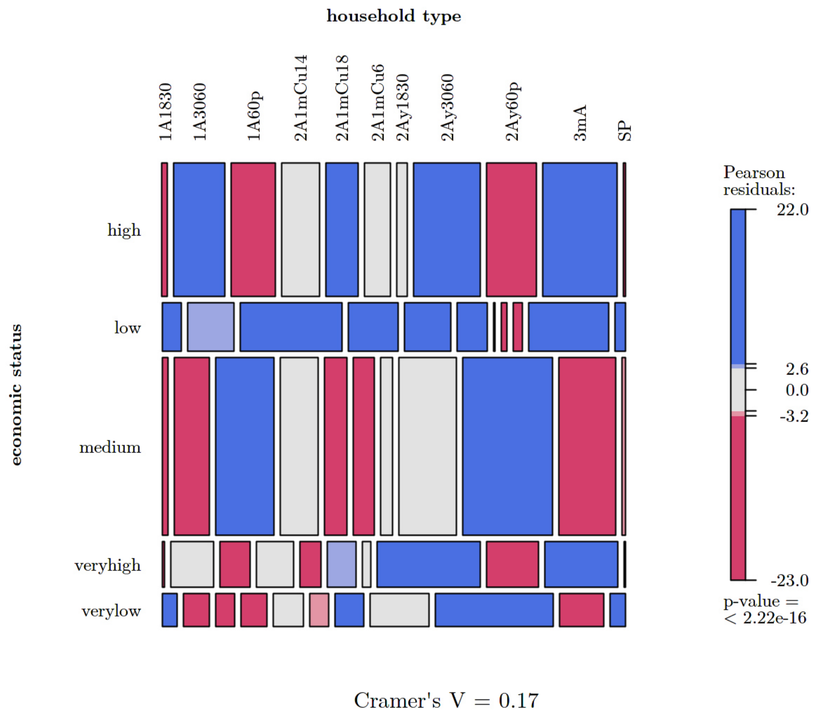


FIGURE 51: HOUSEHOLD LEVEL (χ^2-TEST AND MOSAIC PLOT): MAIN EFFECT OF ECONOMIC STATUS ON HOUSEHOLD TYPE

HL-C2-2: Is the household's economic status dependent on the place of residence?

H_0: *The attribute 'place of residence' is* independent *from the attribute 'economic household status'.*

H_1: *The attribute 'place of residence' is* dependent *on the attribute 'economic household status'.*

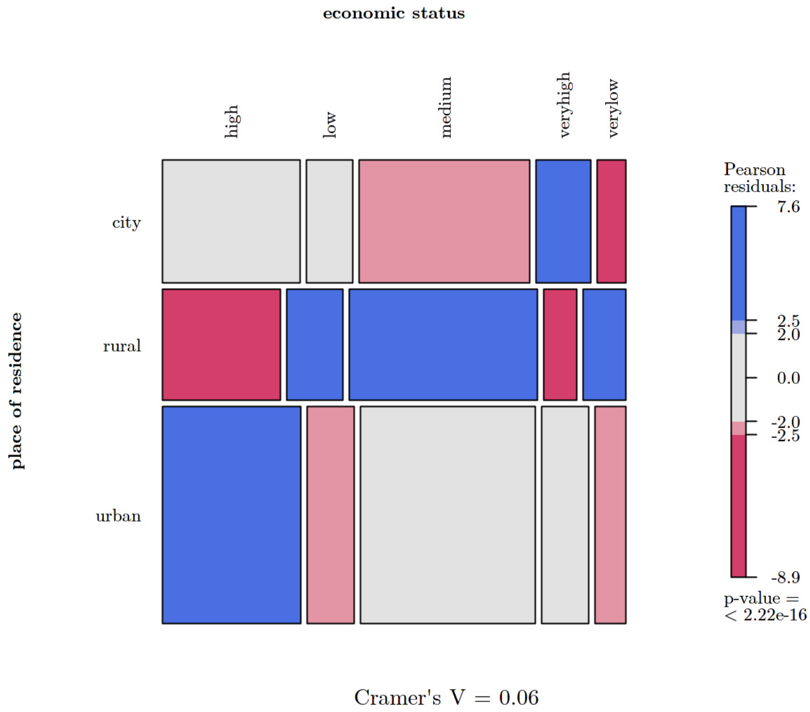


Figure 52: Household level (χ^2-test and mosaic plot): main effect of place of residence on economic status

A.5.2 Vehicle level

VL-C1-2: Is the main user's occupation dependent on the main user's household's economic status?

H_0: *The attribute 'main user occupation' is* <u>*independent*</u> *from the attribute 'economic status'.*

H_1: *The attribute 'main user occupation' is* <u>*dependent*</u> *on the attribute 'economic status'.*

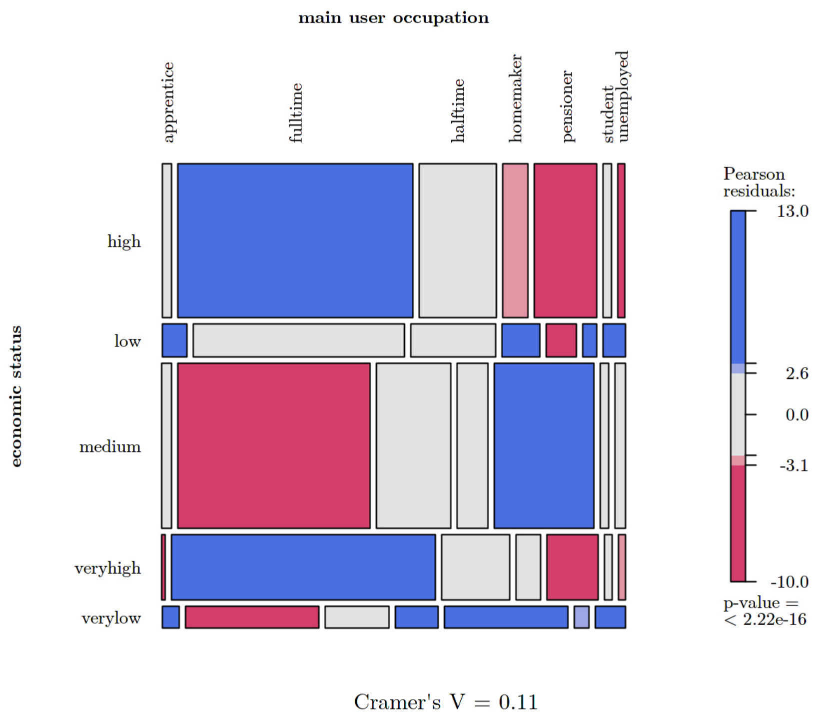


FIGURE 53: VEHICLE LEVEL (χ^2-TEST AND MOSAIC PLOT): MAIN EFFECT OF ECONOMIC STATUS ON MAIN USER OCCUPATION

VL-C1-3: Is the main user's occupation dependent on the main user's household's place of residence?

H_0: *The attribute 'main user occupation' is* <u>*independent*</u> *from the attribute 'place of residence'.*

H_1: *The attribute 'main user occupation' is* <u>*dependent*</u> *on the attribute 'place of residence'.*

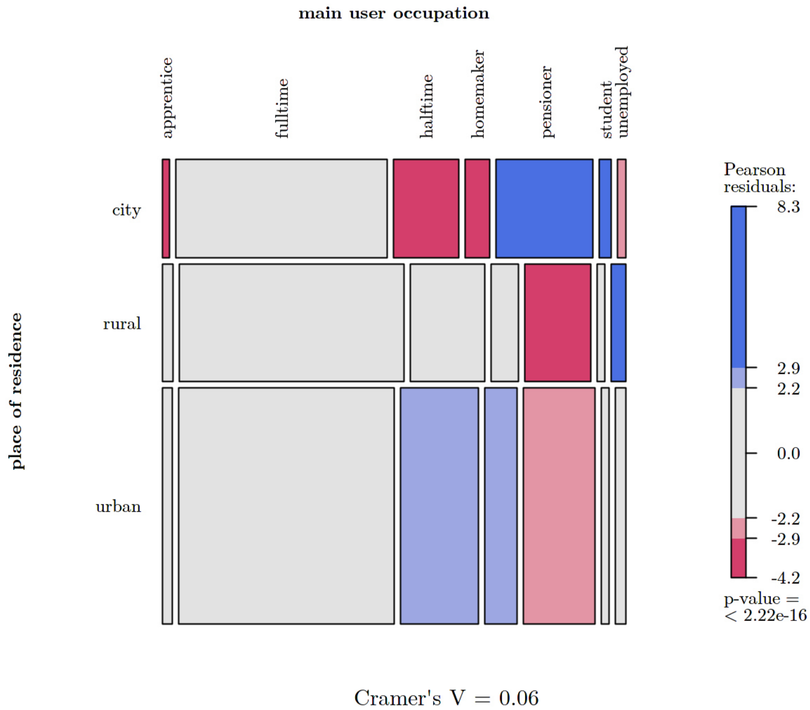


FIGURE 54: VEHICLE LEVEL (χ^2-TEST AND MOSAIC PLOT): MAIN EFFECT OF PLACE OF RESIDENCE ON MAIN USER OCCUPATION

A.5.3 Trip level

TL-C1-4: Is the trip's departure and arrival place on workdays dependent on the main user's occupation?

H_0: *The attribute 'from...to' is <u>independent</u> from the attribute 'main user occupation' controlling for trips on workdays.*

H_1: *The attribute 'from...to' is <u>dependent</u> on the attribute 'main user occupation' controlling for trips on workdays.*

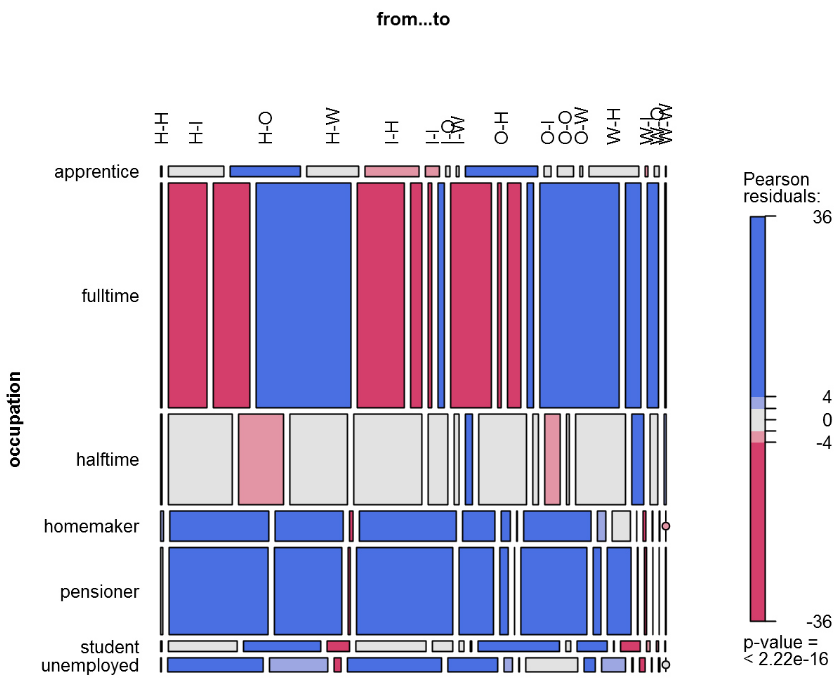


FIGURE 55: TRIP LEVEL (χ^2-TEST AND MOSAIC PLOT): INTERACTION EFFECT OF MAIN USER OCCUPATION ON DEPARTURE ARRIVAL PLACES CONTROLLING FOR WORKDAYS

TL-C1-5: Is the trip's departure and arrival place on Saturdays dependent on the main user's occupation?

H_0: *The attribute 'from...to' is <u>independent</u> from the attribute 'main user occupation' controlling for trips on Saturdays.*

H_1: *The attribute 'from...to' is <u>dependent</u> on the attribute 'main user occupation' controlling for trips on Saturdays.*

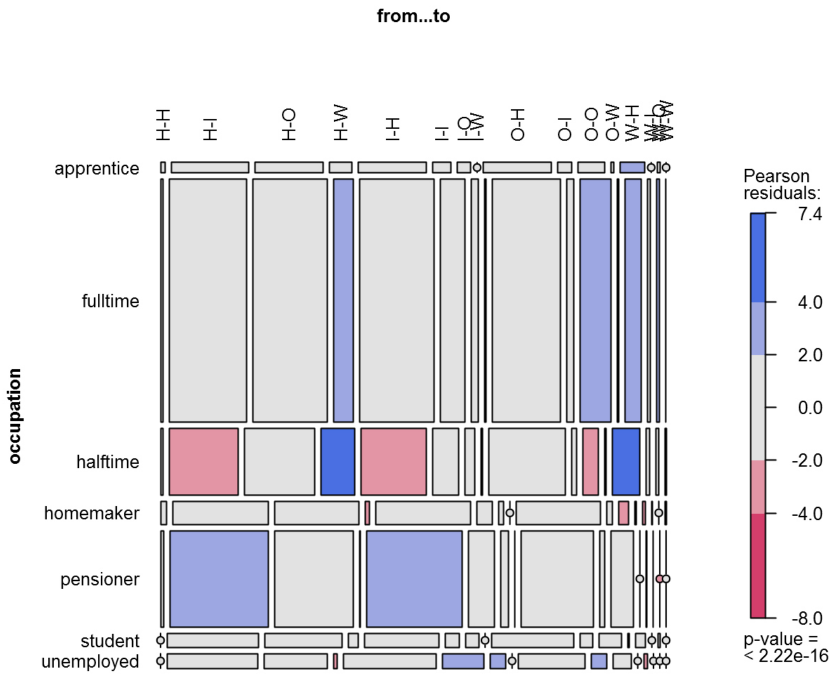


Figure 56: Trip level (χ^2-test and mosaic plot): interaction effect of main user occupation on departure arrival places controlling for Saturdays

TL-C1-6: Is the trip's departure and arrival place on Sundays dependent on the main user's occupation?

H_0: *The attribute 'from...to' is* <u>*independent*</u> *from the attribute 'main user occupation' controlling for trips on Sundays.*

H_1: *The attribute 'from...to' is* <u>*dependent*</u> *on the attribute 'main user occupation' controlling for trips on Sundays.*

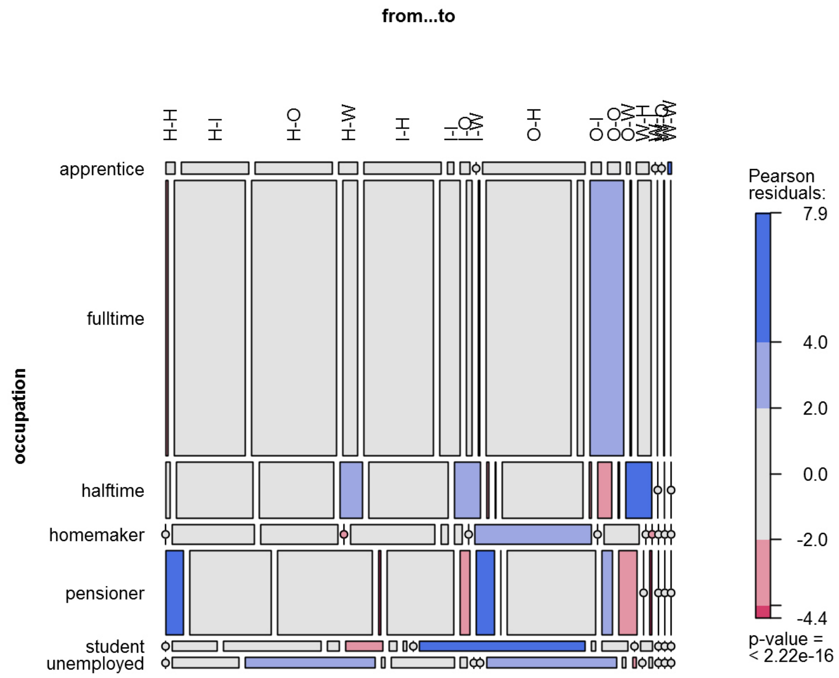


FIGURE 57: TRIP LEVEL (χ^2-TEST AND MOSAIC PLOT): INTERACTION EFFECT OF MAIN USER OCCUPATION ON DEPARTURE ARRIVAL PLACES CONTROLLING FOR SUNDAYS

TL-C2-2: Is the trip's purpose dependent on the weekday?

H_0: *The attribute 'trip purpose' is* *independent* *from the attribute 'weekday'.*

H_1: *The attribute 'trip purpose' is* *dependent* *on the attribute 'weekday'.*

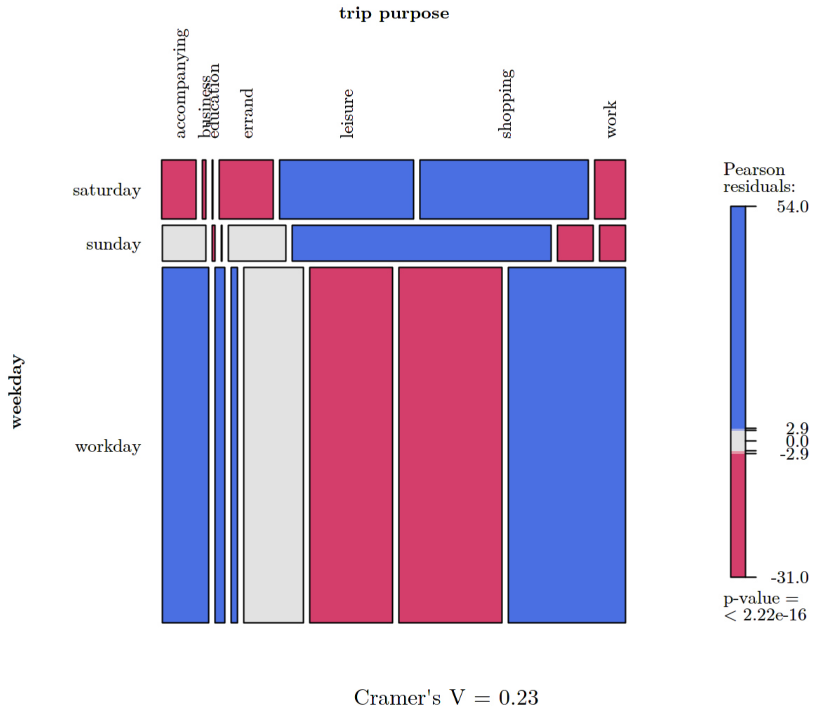


FIGURE 58: TRIP LEVEL (χ^2-TEST AND MOSAIC PLOT): MAIN EFFECT OF WEEKDAY ON TRIP PURPOSE

A.6 Summary tables of main effects

Table 64: Summary on presented main effect results (I)

Research question (coding)	H_0	Decision on H_0 at $\alpha_{local} = 0.05$	Effect size category	Comment
HL-N1-1	*The # of cars of households with a higher 'economic household status' does not tend to be higher than for households with a lower 'economic household status'.*	rejected	large $\lvert\lvert\bar{\delta}\rvert\rvert_\infty = 0.56$	
HL-N1-2	*The # of cars of households with a family 'household type' does not tend to be higher than for households with a non-family 'household type'.*	not rejected	large $\lvert\lvert\bar{\delta}\rvert\rvert_\infty = 0.835$	could be rejected for family households with minimum one underage or adult child neglecting SP households
HL-N1-3	*The # of cars of households with a rural 'place of residence' does not tend to be higher than for households with an urban or city 'place of residence'.*	not rejected	small $\lvert\lvert\bar{\delta}\rvert\rvert_\infty = 0.255$	could be rejected grouping the factor levels 'rural' and 'urban'
HL-C2-1	*The attribute 'household type' is independent from the attribute 'place of residence'.*	rejected	small $V = 0.10$	
VL-N1-1	*The # of car trips per (use) day of primary drivers from households with a higher 'economic household status' does not tend to be higher than for primary drivers from households with a lower 'economic household status'.*	not rejected	negligible $\lvert\lvert\bar{\delta}\rvert\rvert_\infty = 0.075$	
VL-N1-2	*The # of car trips per (use) day of primary drivers from households with a family 'household type' does not tend to be higher than for primary drivers from households with a non-family 'household type'.*	rejected	small $\lvert\lvert\bar{\delta}\rvert\rvert_\infty = 0.22$	
VL-N1-3	*The # of car trips per (use) day of primary drivers from households with a rural 'place of residence' does not tend to be higher than for primary drivers from households with a an urban or city 'place of residence'.*	not rejected	negligible $\lvert\lvert\bar{\delta}\rvert\rvert_\infty = 0.05$	
VL-N1-4	*The # of car trips per (use) day of primary drivers with a homemaker 'main user occupation' does not tend to be higher than for primary drivers with a non-homemaker 'main user occupation'.*	not rejected	small $\lvert\lvert\bar{\delta}\rvert\rvert_\infty = 0.21$	could be rejected grouping the factor levels 'unemployed', 'homemaker' and 'halftime'
VL-N1-5	*The # of car trips per (use) day of primary drivers with a higher 'vehicle use frequency' does not tend to be higher than for primary drivers with a lower 'vehicle use frequency'.*	rejected	small $\lvert\lvert\bar{\delta}\rvert\rvert_\infty = 0.235$	
VL-N1-6	*The # of car trips per (use) day of primary drivers does not tend to be higher in winter than in other 'seasons'.*	not rejected	negligible $\lvert\lvert\bar{\delta}\rvert\rvert_\infty = 0.05$	
VL-N1-7	*The # of car trips per (use) day of primary drivers does not tend to be higher on workdays than on other 'weekdays'.*	rejected	small $\lvert\lvert\bar{\delta}\rvert\rvert_\infty = 0.275$	

Note that influencing factors were considered for synPRO-emobility in descending order regarding their largest pairwise effect sizes (except 'negligible' effects) as long as the smallest resulting sample size of factor level groups was larger than 30.

TABLE 65: SUMMARY ON PRESENTED MAIN EFFECT RESULTS (II)

Research question (coding)	H_0	Decision on H_0 at $\alpha_{local} = 0.05$	Effect size category	Comment
VL-C1-1	*The attribute 'main user occupation' is <u>independent</u> from the attribute 'household type'.*	rejected	medium $V = 0.32$	
VL-C2-1	*The attribute 'main user (vehicle) use frequency' is <u>independent</u> from the attribute 'household type'.*	rejected	small $V = 0.19$	
VL-C2-2	*The attribute 'main user (vehicle) use frequency' is <u>independent</u> from the attribute 'main user occupation'.*	rejected	small $V = 0.25$	
VL-C2-3	*The attribute 'main user (vehicle) use frequency' is <u>independent</u> from the attribute 'place of residence'.*	rejected	negligible $V = 0.07$	
VL-C3-1	*The attribute 'main user (daily vehicle) use' is <u>independent</u> from the attribute 'main user (vehicle) use frequency'.*	rejected	small $V = 0.21$	
VL-C3-2	*The attribute 'main user (daily vehicle) use' is <u>independent</u> from the attribute 'place of residence'.*	rejected	negligible $V = 0.03$	
VL-C3-3	*The attribute 'main user (daily vehicle) use' is <u>independent</u> from the attribute 'weekday'.*	rejected	small $V = 0.16$	
TL-N1-1	*The driven distance to work (or from work home) of primary drivers with a full-time 'main user occupation' does <u>not tend</u> to be longer than for a primary driver with a non-fulltime 'main user occupation'.*	not rejected	small $\|\|\bar{\delta}\|\|_\infty = 0.26$	ambiguous test result
TL-N1-2	*The driven distance to work (or from work home) of primary drivers from households with a rural 'place of residence' does <u>not tend</u> to be longer than for a primary driver from households with a urban or city 'place of residence'.*	not rejected	negligible $\|\|\bar{\delta}\|\|_\infty = 0.085$	
TL-N2-1	*The driven distance of trips with a leisure 'trip purpose' does <u>not tend</u> to be longer than for trips with other 'trip purposes'.*	not rejected	large $\|\|\bar{\delta}\|\|_\infty = 0.625$	could be rejected grouping the factor levels 'education' and 'business'
TL-N2-2	*The driven distance of trips with an outside city 'trip distance category' does <u>not tend</u> to be longer than for trips with an inside city or unknown 'trip distance category'.*	rejected	large $\|\|\bar{\delta}\|\|_\infty = 0.625$	

Note that influencing factors were considered for synPRO-emobility in descending order regarding their largest pairwise effect sizes (except 'negligible' effects) as long as the smallest resulting sample size of factor level groups was larger than 30.

Table 66: Summary on presented main effect results (III)

Research question (coding)	H_0	Decision on H_0 at $\alpha_{local} = 0.05$	Effect size category	Comment
TL-N2-3	*The driven distance of trips driven on a day with only one or two 'trips per day' does not tend to be longer than for trips driven on a day with a larger 'number of trips per day'.*	rejected	medium $\|\|\bar{\delta}\|\|_\infty = 0.37$	
TL-N2-4	*The driven distance does not tend to be shorter for trips driven on workdays than on other 'weekdays'.*	not rejected	small $\|\|\bar{\delta}\|\|_\infty = 0.215$	could be rejected grouping the factor levels 'workday' and 'Saturday'
TL-N2-5	*The driven distance does not tend to be shorter for trips driven in winter than in other 'seasons'.*	not rejected	negligible $\|\|\bar{\delta}\|\|_\infty = 0.05$	
TL-N3-1	*The departure time to work (of the first trip per day) of primary drivers with a fulltime 'main user occupation' does not tend to be earlier than for primary drivers with a non-fulltime 'main user occupation'.*	not rejected	medium $\|\|\bar{\delta}\|\|_\infty = 0.355$	could be rejected grouping the factor levels 'fulltime' and 'apprentice'
TL-N3-2	*The departure time to work (of the first trip per day) of primary drivers with a rural 'place of residence' does not tend to be earlier than for primary drivers with an urban or city 'place of residence'.*	not rejected	small $\|\|\bar{\delta}\|\|_\infty = 0.13$	could be rejected grouping the factor levels 'city' and 'urban'
TL-N3-3	*The departure time to work (of the first trip per day) of trips driven on a workday does not tend to be earlier than for trips driven on a Saturday or Sunday.*	not rejected	small $\|\|\bar{\delta}\|\|_\infty = 0.275$	could be rejected grouping the factor levels 'workday' and 'Saturday'
TL-N3-4	*The departure time to work (of the first trip per day) does not tend to be earlier for trips driven in winter than in other 'seasons'.*	not rejected	n/c	
TL-N4-1	*The departure time (of the first trip per day) of trips with a leisure 'trip purpose' does not tend to be later than for trips with other 'trip purposes'.*	rejected	large $\|\|\bar{\delta}\|\|_\infty = 0.785$	
TL-N4-2	*The departure time (of the first trip per day) for trips driven on a day with only one or two 'trips per day' does not tend to be earlier than for trips driven on a day with a larger 'number of trips per day'.*	rejected	large $\|\|\bar{\delta}\|\|_\infty = 0.595$	
TL-N4-3	*The departure time (of the first trip per day) of trips driven on a workday does not tend to be earlier than for trips driven on a Saturday or Sunday.*	not rejected	small $\|\|\bar{\delta}\|\|_\infty = 0.23$	could be rejected grouping the factor levels 'workday' and 'Saturday'

Note that influencing factors were considered for synPRO-emobility in descending order regarding their largest pairwise effect sizes (except 'negligible' effects) as long as the smallest resulting sample size of factor level groups was larger than 30.

Table 67: Summary on presented main effect results (IV)

Research question (coding)	H_0	Decision on H_0 at $\alpha_{local} = 0.05$	Effect size category	Comment
TL-N4-4	*The departure time (of the first trip per day) of trips driven by a primary driver with a rural 'place of residence' does not tend to be earlier than for primary drivers with an urban or city 'place of residence'.*	not rejected	negligible $\|\|\bar{\delta}\|\|_\infty = 0.09$	
TL-N4-5	*The departure time (of the first trip per day) does not tend to be smaller for trips driven in winter than in other 'seasons'.*	not rejected	n/c	
TL-N5-1	*The driving time to work (or from work home) of primary drivers with a fulltime 'main user occupation' does not tend to be longer than for primary drivers with a non-fulltime 'main user occupation'.*	not rejected	small $\|\|\bar{\delta}\|\|_\infty = 0.23$	ambiguous test result
TL-N5-2	*The driving time to work (or from work home) of primary drivers with a rural 'place of residence' does not tend to be longer than for primary drivers with an urban or city 'place of residence'.*	not rejected	small $\|\|\bar{\delta}\|\|_\infty = 0.115$	could be rejected for households with a city 'place of residence'
TL-N5-3	*The driving time to work (or from work home) of trips driven on a workday does not tend to be longer than for trips driven on a Saturday or Sunday.*	not rejected	small $\|\|\bar{\delta}\|\|_\infty = 0.255$	could be rejected grouping the factor levels 'Saturday' and 'Sunday'
TL-N5-4	*The driving time to work (or from work home) does not tend to be longer for trips driven in winter than in other 'seasons'.*	not rejected	negligible $\|\|\bar{\delta}\|\|_\infty = 0.045$	
TL-N6-1	*The driving time of trips with a leisure 'trip purpose' does not tend to be longer than for trips with other 'trip purposes'.*	not rejected	large $\|\|\bar{\delta}\|\|_\infty = 0.625$	could be rejected grouping the factor levels 'business' and 'education'
TL-N6-2	*The driving time of trips with an outside city 'trip distance category' does not tend to be longer than for trips with an inside city or unknown 'trip distance category'.*	rejected	large $\|\|\bar{\delta}\|\|_\infty = 0.6$	
TL-N6-3	*The driving time of trips driven on a day with only one or two 'trips per day' does not tend to be longer than for trips driven on a day with another 'number of trips per day'.*	rejected	medium $\|\|\bar{\delta}\|\|_\infty = 0.375$	
TL-N6-4	*The driving time does not tend to be shorter for trips driven on workdays than on other 'weekdays'.*	not rejected	small $\|\|\bar{\delta}\|\|_\infty = 0.155$	could be rejected grouping the factor levels 'workday' and 'Saturday'
TL-N6-5	*The driving time does not tend to be shorter for trips driven in winter than in other 'seasons'.*	not rejected	negligible $\|\|\bar{\delta}\|\|_\infty = 0.05$	

Note that influencing factors were considered for synPRO-emobility in descending order regarding their largest pairwise effect sizes (except 'negligible' effects) as long as the smallest resulting sample size of factor level groups was larger than 30.

Table 68: Summary on presented main effect results (V)

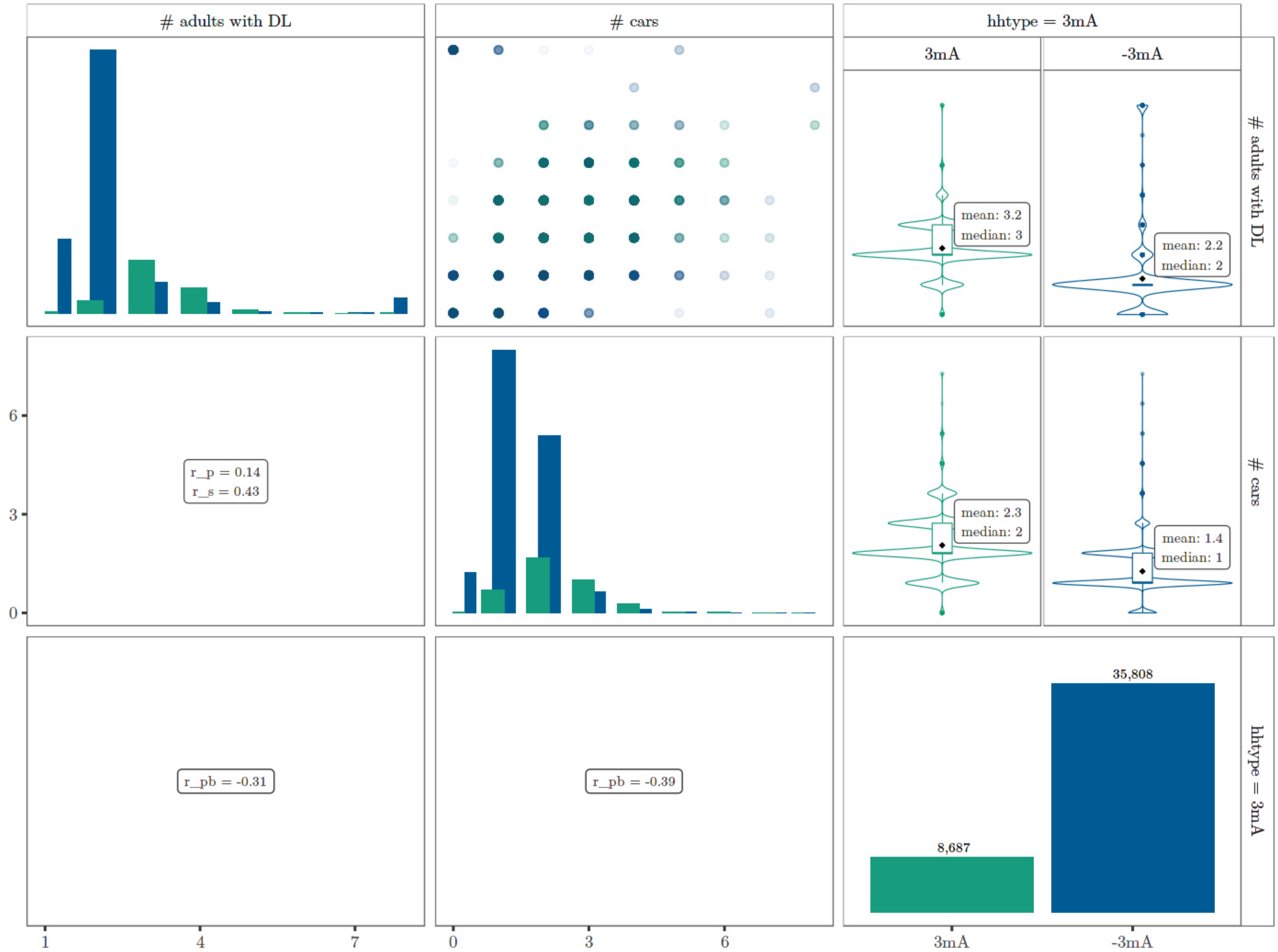
Research question (coding)	H_0	Decision on H_0 at $\alpha_{local} = 0.05$	Effect size category	Comment
TL-N7-1	*The parking time at work of primary drivers with a fulltime 'main user occupation' does not tend to be longer than for primary drivers with a non-fulltime 'main user occupation'.*	rejected	large $\lvert\lvert\bar{\delta}\rvert\rvert_\infty = 0.515$	
TL-N7-2	*The parking time at work of trips driven on a workday does not tend to be longer than for trips driven on a Saturday or Sunday.*	not rejected	small $\lvert\lvert\bar{\delta}\rvert\rvert_\infty = 0.27$	could be rejected grouping the factor levels 'Saturday' and 'Sunday'
TL-N8-1	*The parking time of trips with a leisure 'trip purpose' does not tend to be longer than for trips with other 'trip purposes'.*	not rejected	large $\lvert\lvert\bar{\delta}\rvert\rvert_\infty = 0.755$	could be rejected for trips with the trip purpose 'education'
TL-N8-2	*The parking time of trips driven on a day with only one or two 'trips per day' does not tend to be longer than for trips driven on a day with another 'number of trips per day'.*	rejected	medium $\lvert\lvert\bar{\delta}\rvert\rvert_\infty = 0.395$	
TL-N8-3	*The parking time does not tend to be shorter for trips driven on workdays than on other 'weekdays'.*	not rejected	small $\lvert\lvert\bar{\delta}\rvert\rvert_\infty = 0.215$	could be rejected grouping the factor levels 'workday' and 'Saturday'
TL-N8-4	*The parking time does not tend to be shorter for trips driven in winter than in other 'seasons'.*	not rejected	negligible $\lvert\lvert\bar{\delta}\rvert\rvert_\infty = 0.075$	
TL-C1-1	*The attribute 'from...to' is independent from the attribute 'main user occupation'.*	not rejected	small $V = 0.11$	
TL-C1-2	*The attribute 'from...to' is independent from the attribute 'trip index'.*	rejected	large $V = 0.52$	
TL-C1-3	*The attribute 'from...to' is independent from the attribute 'weekday'.*	rejected	small $V = 0.17$	
TL-C2-1	*The attribute 'trip purpose' is independent from the attribute 'from...to'.*	rejected	medium $V = 0.4$	

Note that influencing factors were considered for synPRO-emobility in descending order regarding their largest pairwise effect sizes (except 'negligible' effects) as long as the smallest resulting sample size of factor level groups was larger than 30.

B Appendix for Chapter 4

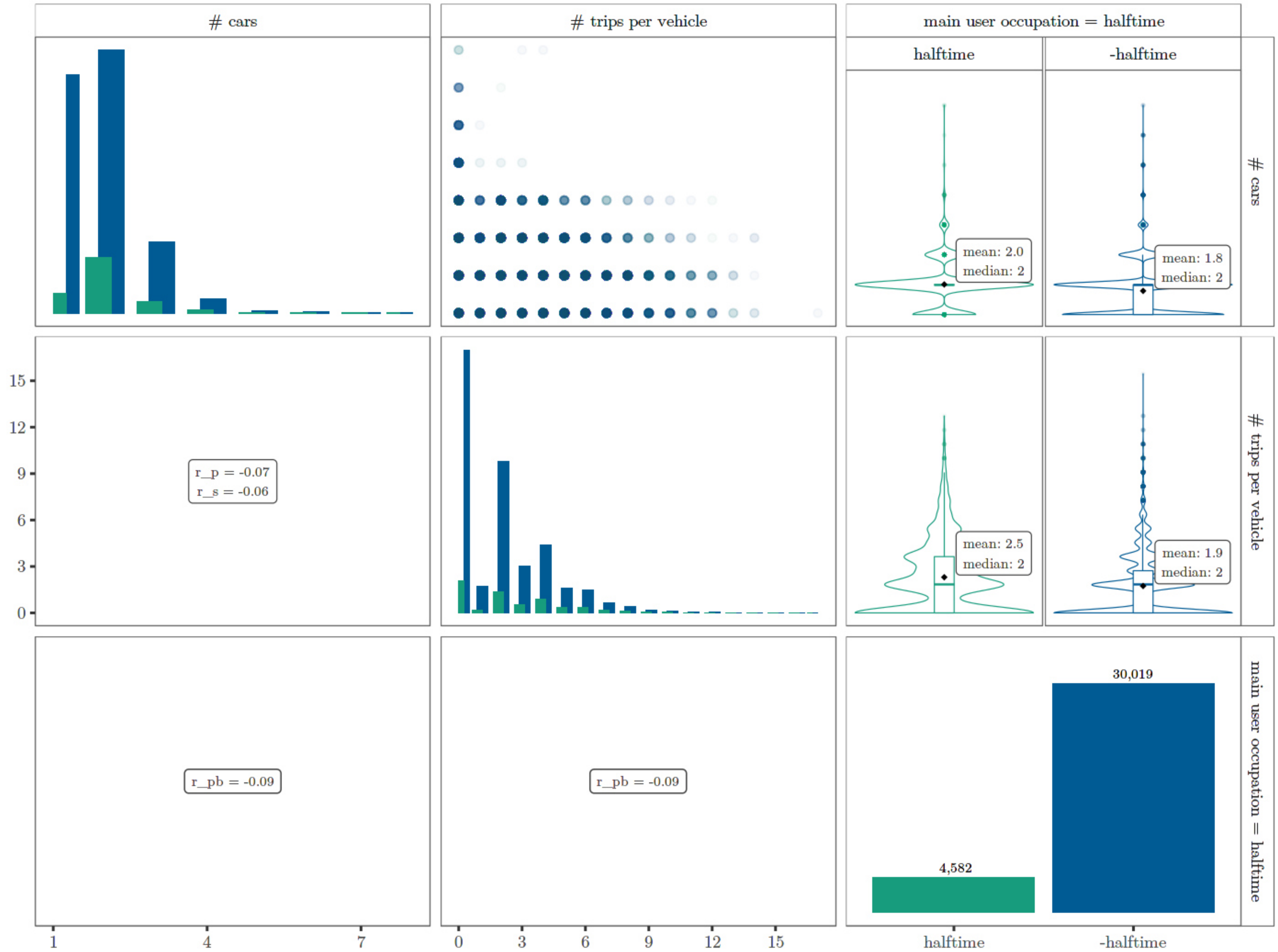
B.1 Selected correlation matrices

Figure 59: Correlation matrix for number of adults with a driving license and number of cars per household for households with and without minimum 3 adult households members



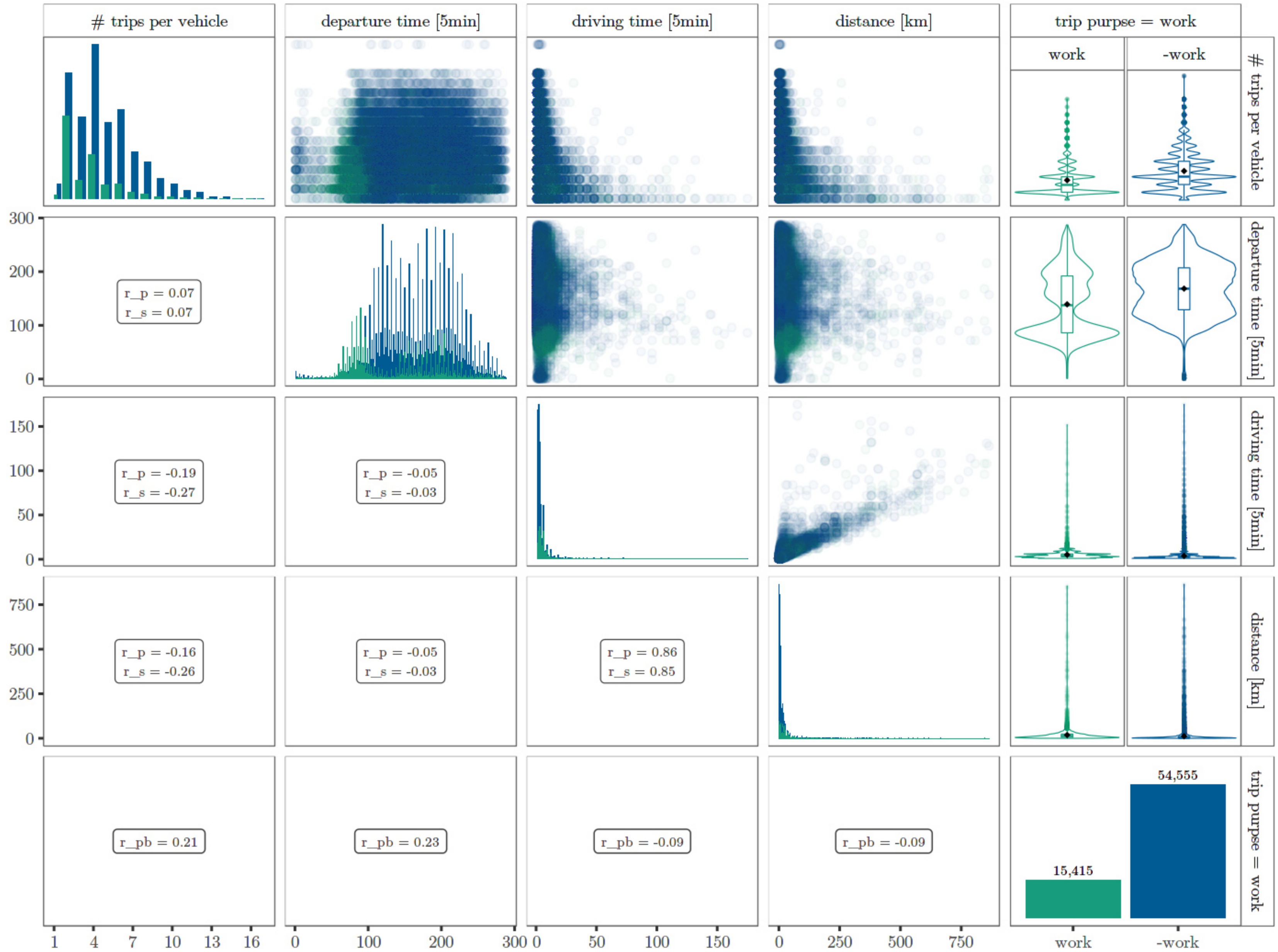
r_p : Pearson's correlation coefficient, r_s : Spearman's rank correlation coefficient, r_{pb} : Point-biserial correlation coefficient

Figure 60: Correlation matrix for number of cars per household and number of trips per (use) day for primary drivers halftime occupied or not halftime occupied



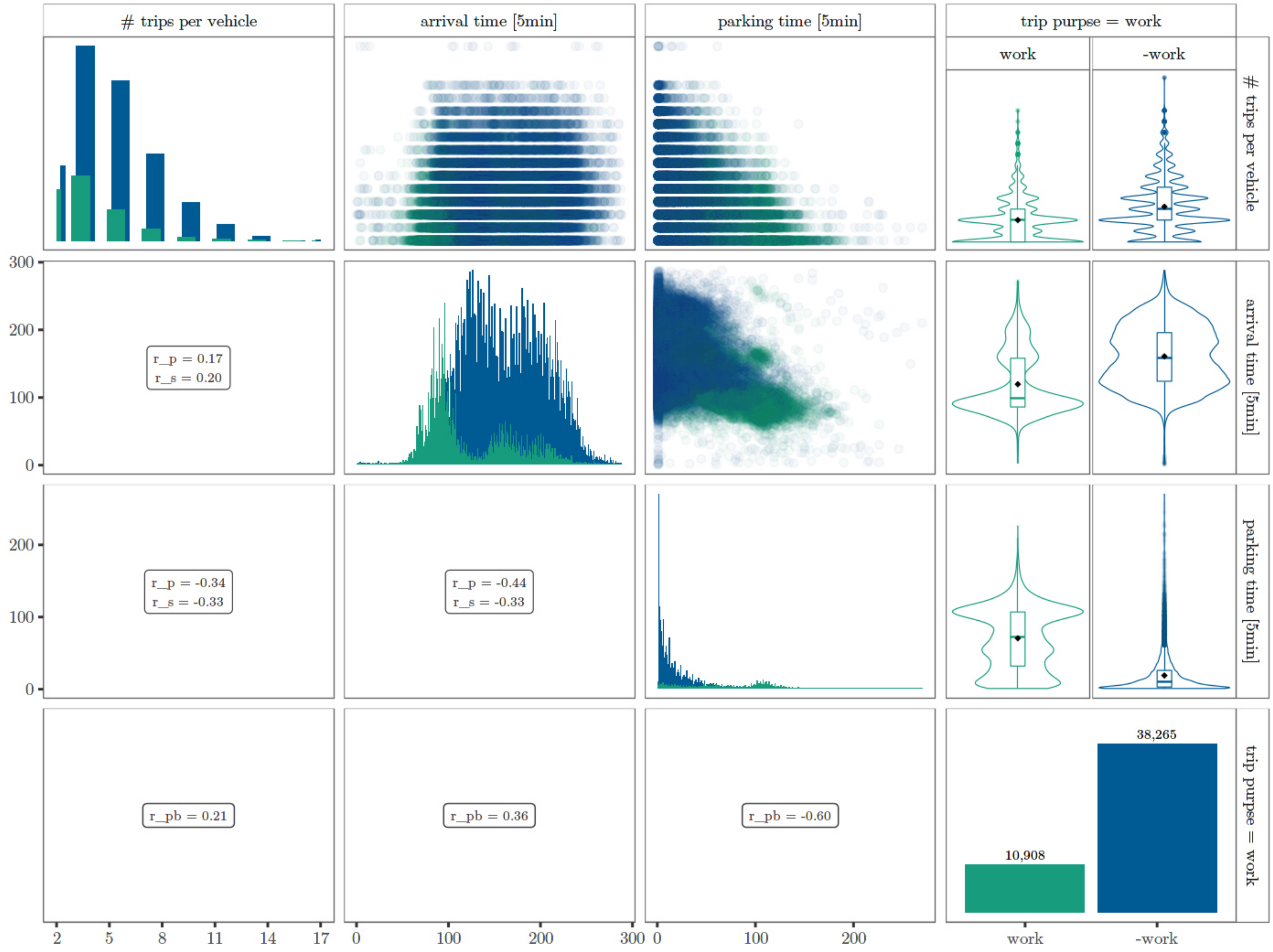
r_p : Pearson's correlation coefficient, r_s : Spearman's rank correlation coefficient, r_{pb} : Point-biserial correlation coefficient

Figure 61: Correlation matrix for number of car trips per (use) day, departure time, driving time and driven distance for trips with and without purpose 'work'



r_p : Pearson's correlation coefficient, r_s : Spearman's rank correlation coefficient, r_{pb} : Point-biserial correlation coefficient

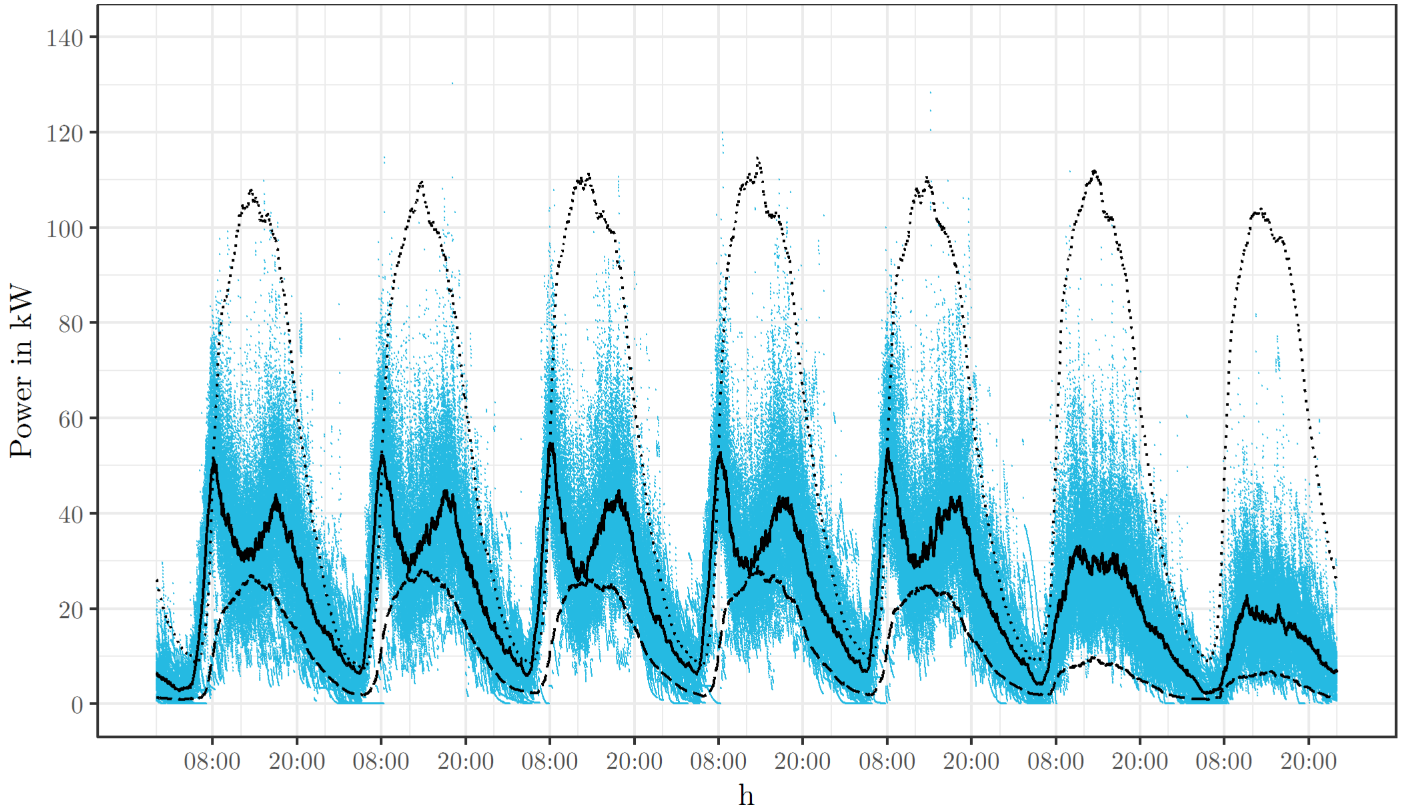
Figure 62: Correlation matrix for number of car trips per (use) day, arrival time, parking time for trips with and without purpose 'work'



r_p : Pearson's correlation coefficient, r_s : Spearman's rank correlation coefficient, r_{pb} : Point-biserial correlation coefficient

B.2 Synthetic load profiles

Figure 63: synPRO-emobility Simulation Results: Scenario 'P0' + Always Charging Upon Arrival, Average Load of 100 BEV for 52 Weeks (364 Days) Aggregated Over all Charging Locations

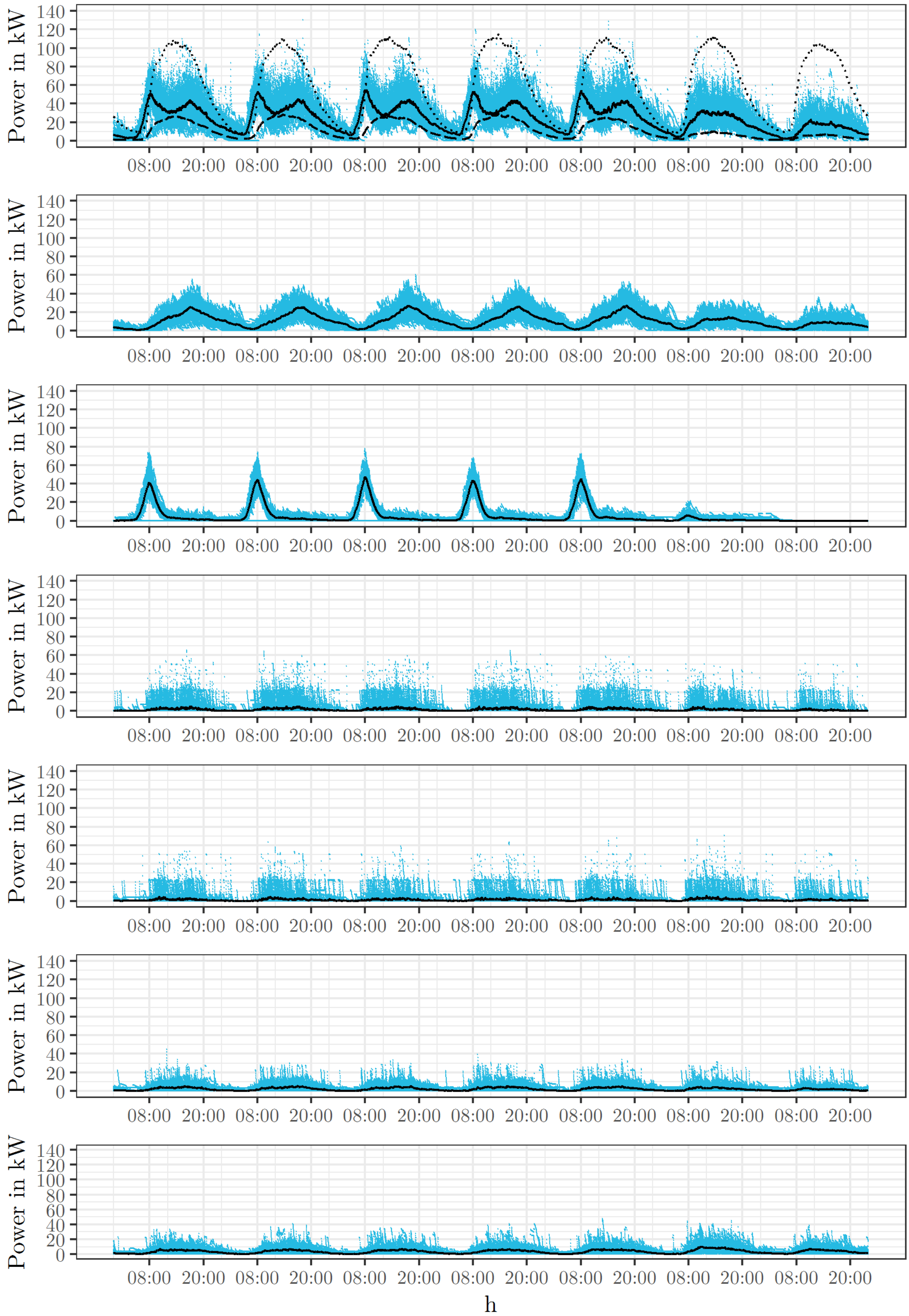


Total annual values
for 100 BEV:
Pmax in kW = 130
Ech in kWh = 210,290
Eimc in kWh = 14,199
Esdc in kWh = 50,985
Econ in kWh = 173,831
No. of charging = 81,154

Daily average per BEV:
Ech in kWh = 5.78
Eimc in kWh = 0.39
Esdc in kWh = 1.40
Econ in kWh = 4.78
No. of charging = 2.23

Blue dots: single active power charging curves of synPRO-emobility
Solid line: average load of synPRO-emobility
Dotted line: average load with no. of charging per vehicle and day $\xi_d = 1.5378$ of Schäuble et al. (2017*b*, p. 262)
Dashed line: average load with no. of charging per vehicle and day drawn from the empirical distribution $\xi_d(100)$ of Schäuble et al. (2017*b*, p. 262)
No. of charging: calculated without intermediate charging

Figure 64: synPRO-emobility Simulation Results: Scenario 'P0' + Always Charging Upon Arrival, Average Load of 100 BEV for 52 Weeks (364 Days), Aggregated and Distinct Charging Locations



Plot order (from above): aggregated load, H, W, POP-IC, POP-OC, SWE-IC, SWE-OC

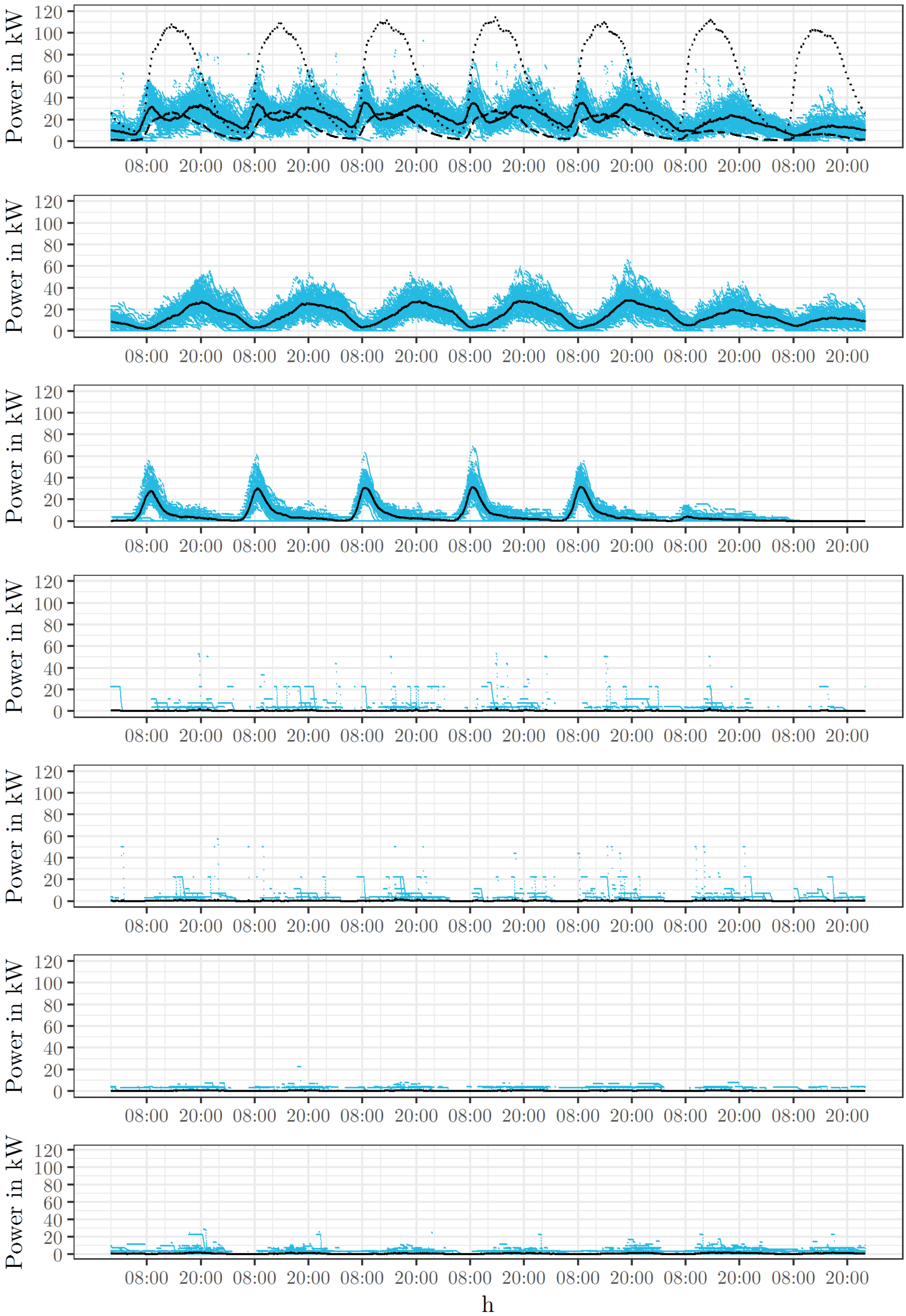
Blue dots: single active power charging curves of synPRO-emobility

Solid line: average load of synPRO-emobility

Dotted line: average load with no. of charging per vehicle and day $\xi_d = 1.5378$ of Schäuble et al. (2017*b*, p. 262)

Dashed line: average load with no. of charging per vehicle and day drawn from the empirical distribution $\xi_d(100)$ of Schäuble et al. (2017*b*, p. 262)

Figure 66: synPRO-emobility Simulation Results: Scenario 'P0' + Connection Indifference Levels in %-SOC: 50 (H), 50 (W), 20 (POP), 5 (SWE), Average Load of 100 BEV from 2Am1Cu18 Households for 52 Weeks (364 Days), Aggregated and Distinct Charging Locations



Plot order (from above): aggregated load, H, W, POP-IC, POP-OC, SWE-IC, SWE-OC

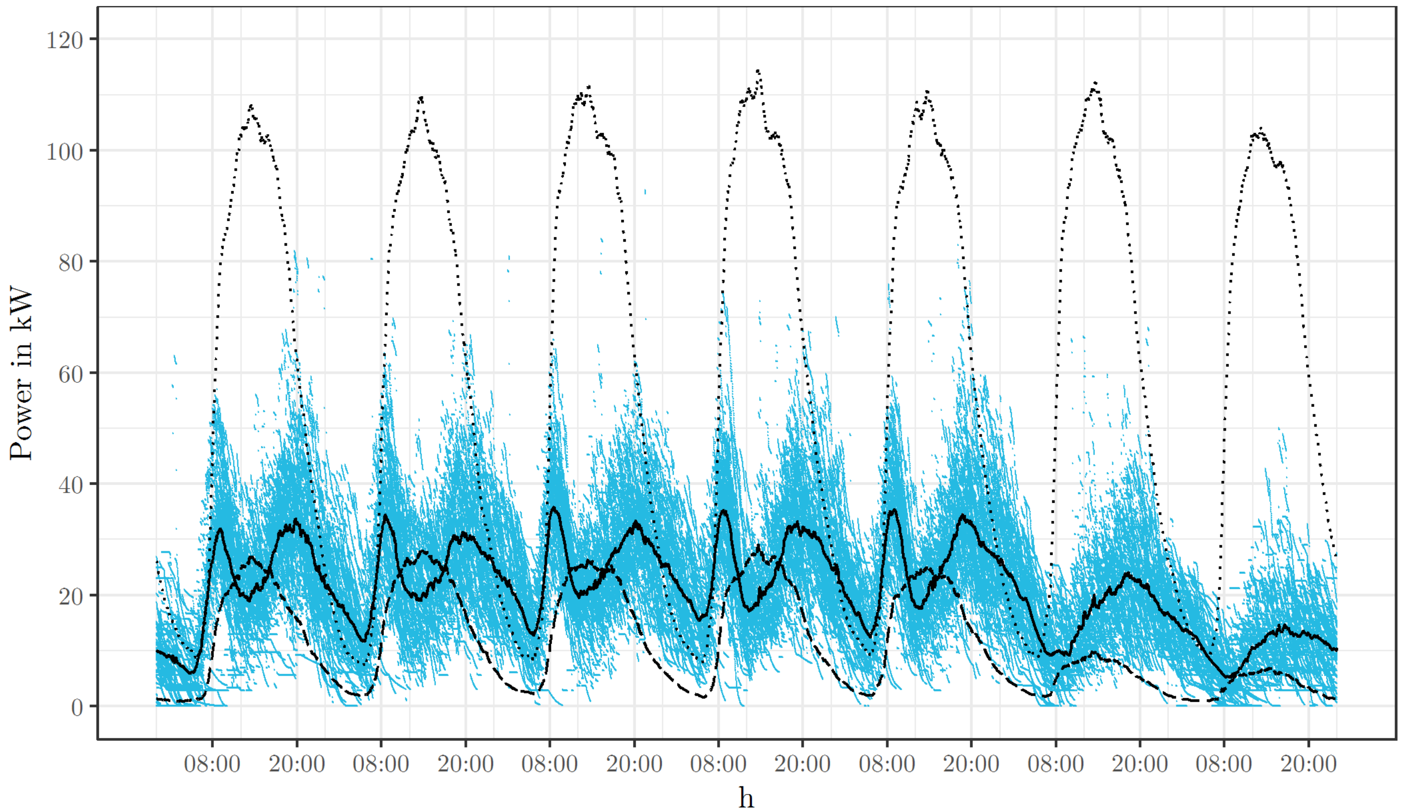
Blue dots: single active power charging curves of synPRO-emobility

Solid line: average load of synPRO-emobility

Dotted line: average load with no. of charging per vehicle and day $\xi_d = 1.5378$ of Schäuble et al. (2017*b*, p. 262)

Dashed line: average load with no. of charging per vehicle and day drawn from the empirical distribution $\xi_d(100)$ of Schäuble et al. (2017*b*, p. 262)

Figure 65: synPRO-emobility Simulation Results: Scenario 'P0' + Connection Indifference Levels in %-SOC: 50 (H), 50 (W), 20 (POP), 5 (SWE), Average Load of 100 BEV from 2Am1Cu18 Households for 52 Weeks (364 Days) Aggregated Over all Charging Locations

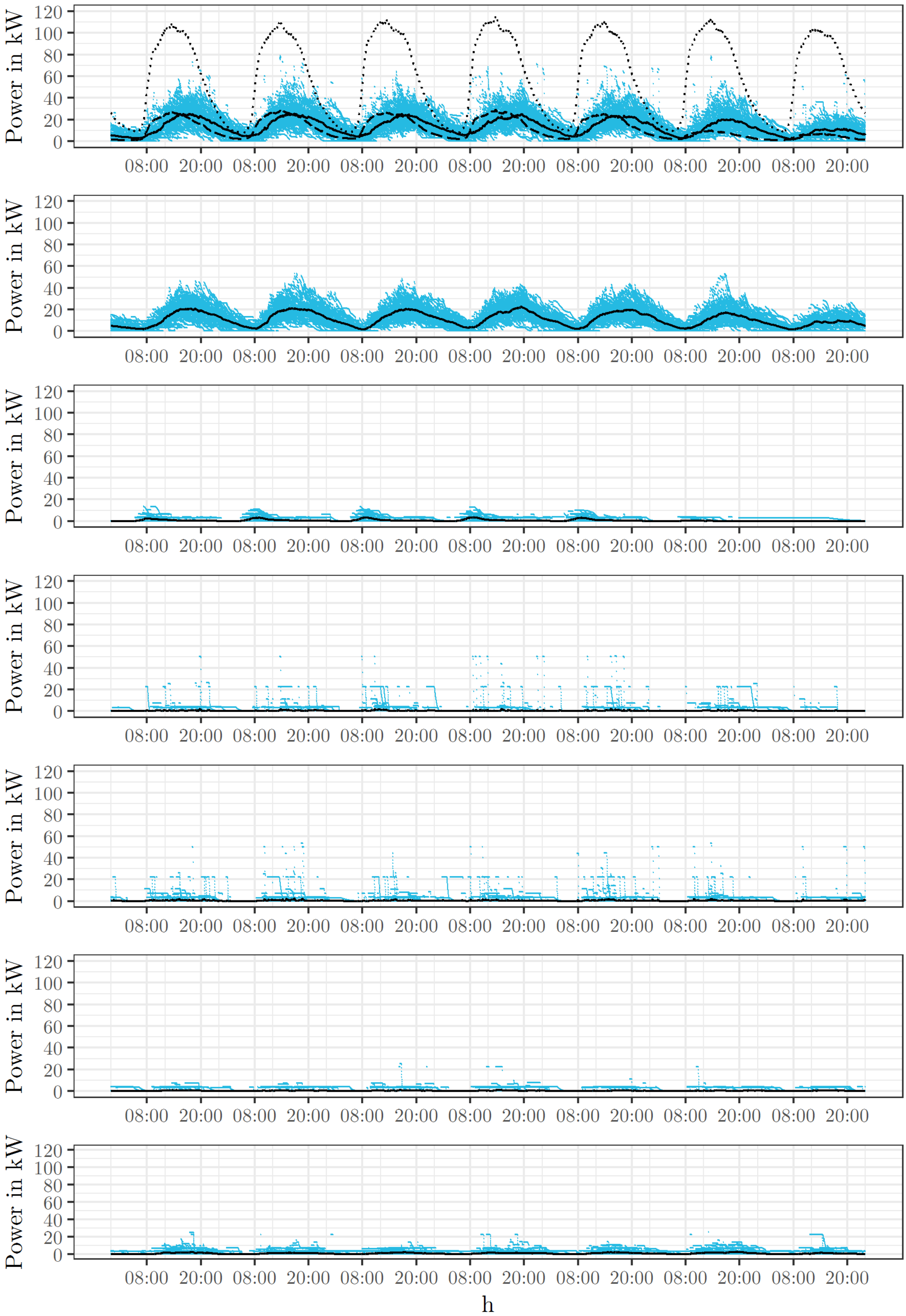


Total annual values
for 100 BEV:
Pmax in kW = 93
Ech in kWh = 184,231
Eimc in kWh = 21,592
Esdc in kWh = 10,111
Econ in kWh = 196,437
No. of charging = 18,401

Daily average per BEV:
Ech in kWh = 5.06
Eimc in kWh = 0.59
Esdc in kWh = 0.28
Econ in kWh = 5.40
No. of charging = 0.51

Blue dots: single active power charging curves of synPRO-emobility
Solid line: average load of synPRO-emobility
Dotted line: average load with no. of charging per vehicle and day $\xi_d = 1.5378$ of Schäuble et al. (2017*b*, p. 262)
Dashed line: average load with no. of charging per vehicle and day drawn from the empirical distribution $\xi_d(100)$ of Schäuble et al. (2017*b*, p. 262)
No. of charging: calculated without intermediate charging

Figure 70: synPRO-emobility Simulation Results: Scenario 'P0' + Connection Indifference Levels in %-SOC: 50 (H), 50 (W), 20 (POP), 5 (SWE), Average Load of 100 BEV from 2Ay60p Households for 52 Weeks (364 Days), Aggregated and Distinct Charging Locations



Plot order (from above): aggregated load, H, W, POP-IC, POP-OC, SWE-IC, SWE-OC

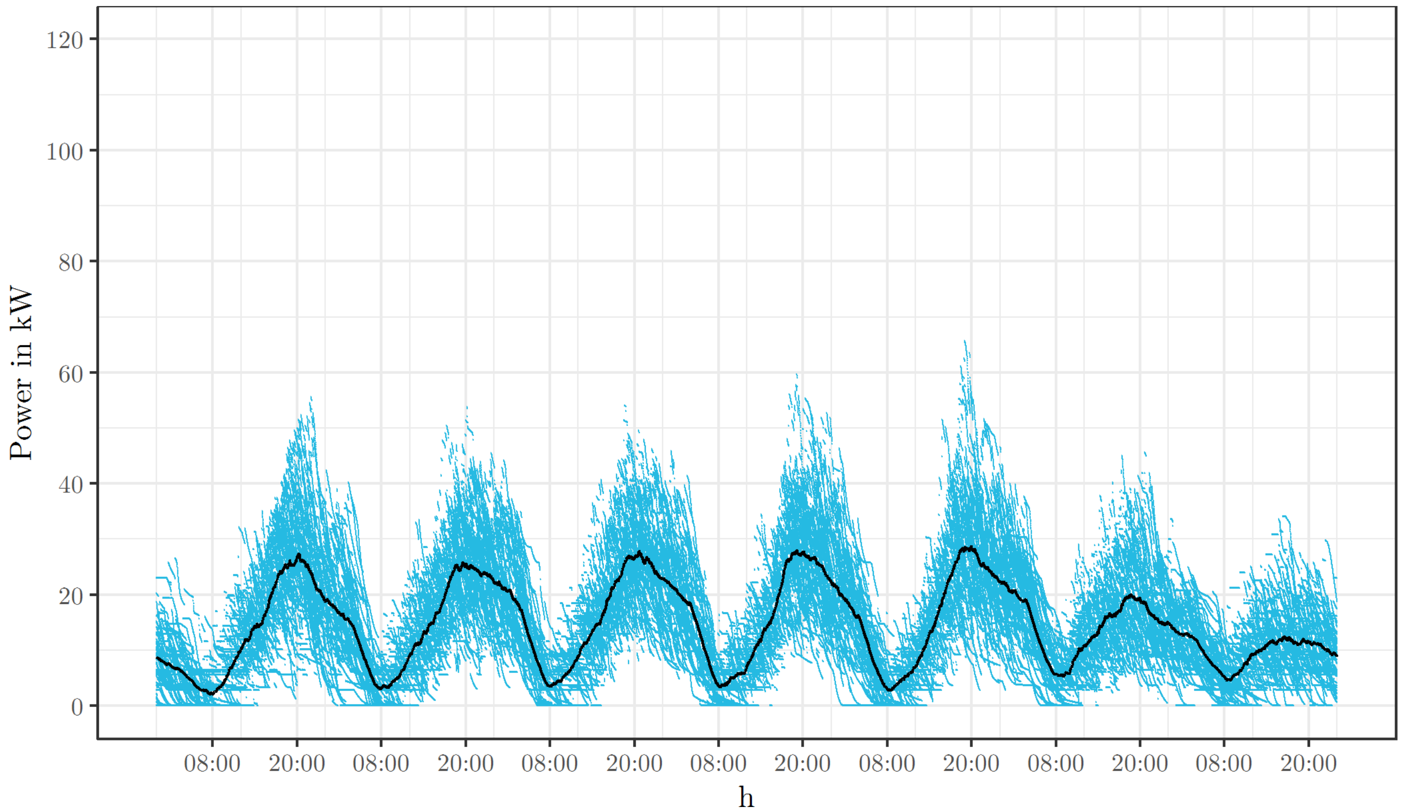
Blue dots: single active power charging curves of synPRO-emobility

Solid line: average load of synPRO-emobility

Dotted line: average load with no. of charging per vehicle and day $\xi_d = 1.5378$ of Schäuble et al. (2017*b*, p. 262)

Dashed line: average load with no. of charging per vehicle and day drawn from the empirical distribution $\xi_d(100)$ of Schäuble et al. (2017*b*, p. 262)

Figure 67: synPRO-emobility Simulation Results: Scenario 'P0' + Connection Indifference Levels in %-SOC: 50 (H), 50 (W), 20 (POP), 5 (SWE), Average Load of 100 BEV from 2Am1Cu18 Households for 52 Weeks (364 Days), Charging Location (H)

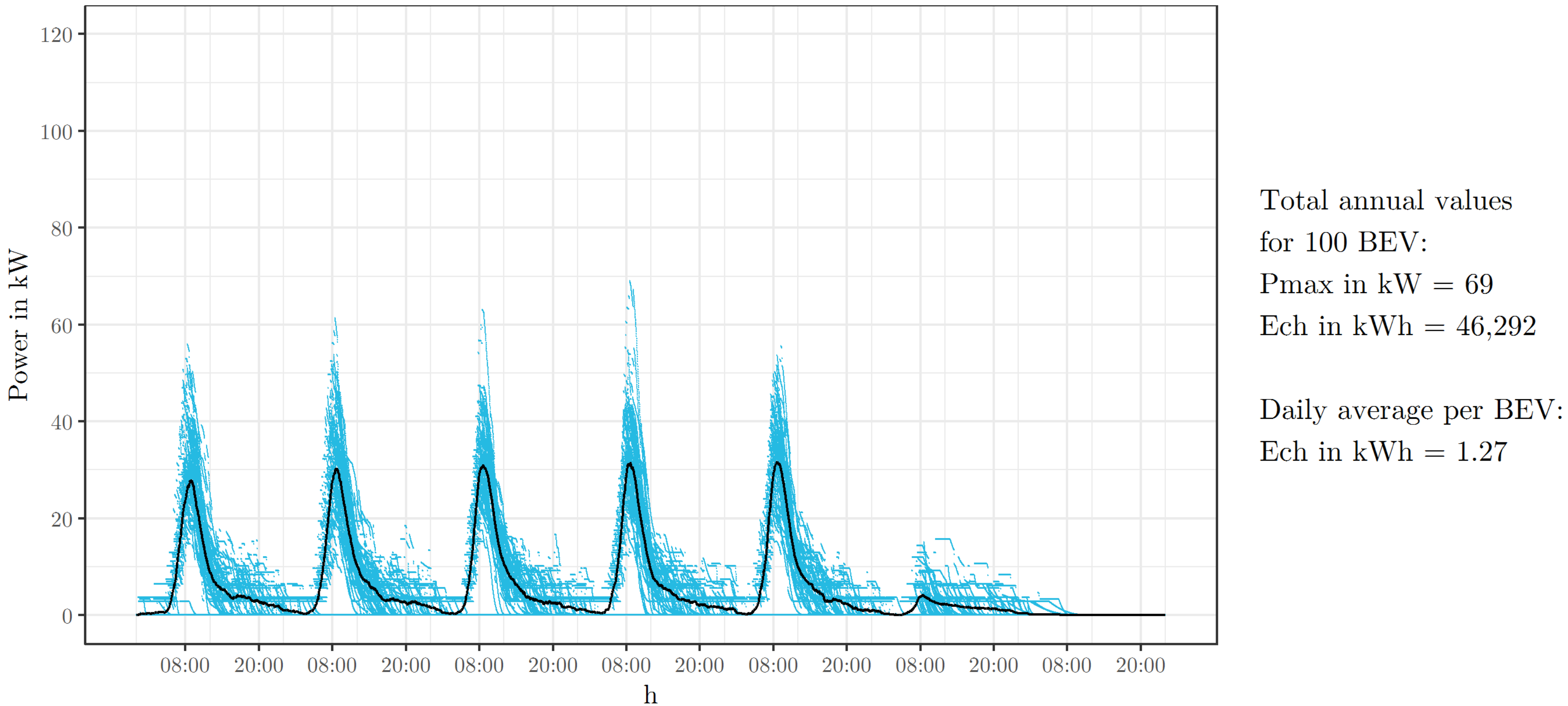


Total annual values
for 100 BEV:
Pmax in kW = 66
Ech in kWh = 126,080

Daily average per BEV:
Ech in kWh = 3.46

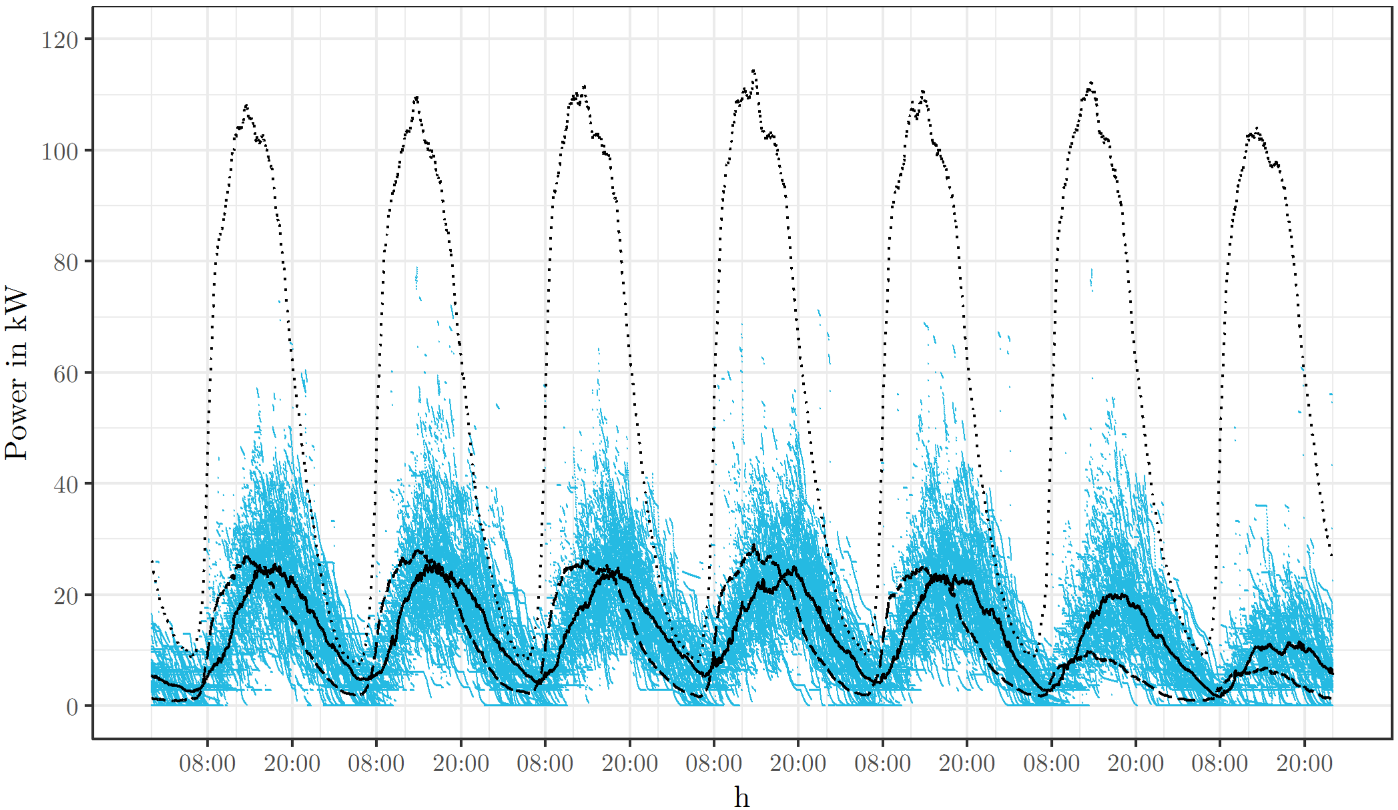
Blue dots: single active power charging curves of synPRO-emobility
Solid line: average load of synPRO-emobility
Dotted line: average load with no. of charging per vehicle and day $\xi_d = 1.5378$ of Schäuble et al. (2017*b*, p. 262)
Dashed line: average load with no. of charging per vehicle and day drawn from the empirical distribution $\xi_d(100)$ of Schäuble et al. (2017*b*, p. 262)
No. of charging: calculated without intermediate charging

Figure 68: synPRO-emobility Simulation Results: Scenario 'P0' + Connection Indifference Levels in %-SOC: 50 (H), 50 (W), 20 (POP), 5 (SWE), Average Load of 100 BEV from 2Am1Cu18 Households for 52 Weeks (364 Days), Charging Location (W)



Blue dots: single active power charging curves of synPRO-emobility
Solid line: average load of synPRO-emobility
Dotted line: average load with no. of charging per vehicle and day $\xi_d = 1.5378$ of Schäuble et al. (2017*b*, p. 262)
Dashed line: average load with no. of charging per vehicle and day drawn from the empirical distribution $\xi_d(100)$ of Schäuble et al. (2017*b*, p. 262)
No. of charging: calculated without intermediate charging

Figure 69: synPRO-emobility Simulation Results: Scenario 'P0' + Connection Indifference Levels in %-SOC: 50 (H), 50 (W), 20 (POP), 5 (SWE), Average Load of 100 BEV from 2Ay60p Households for 52 Weeks (364 Days) Aggregated Over all Charging Locations

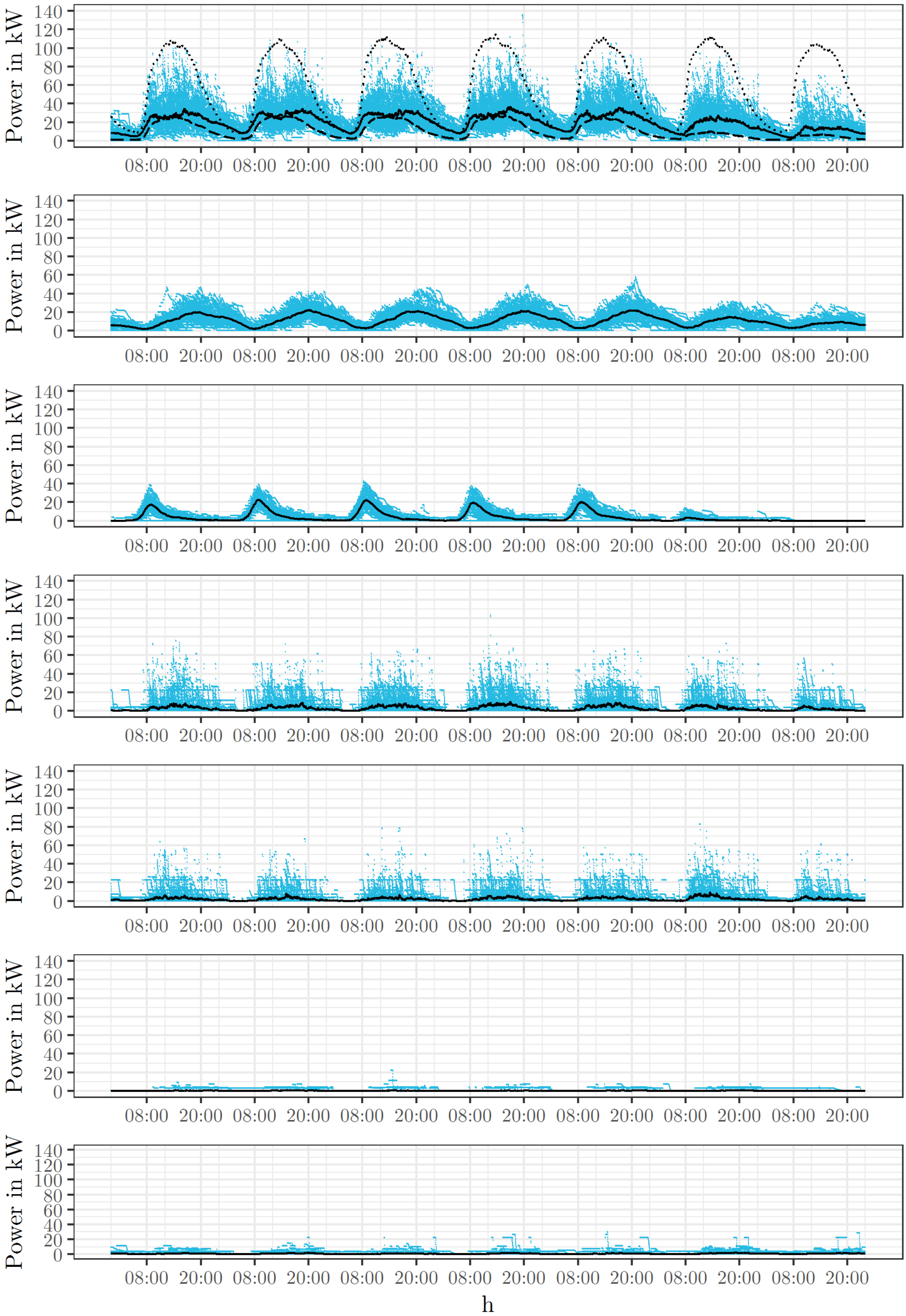


Total annual values for 100 BEV:
Pmax in kW = 79
Ech in kWh = 115,037
Eimc in kWh = 22,207
Esdc in kWh = 7,039
Econ in kWh = 130,807
No. of charging = 11,709

Daily average per BEV:
Ech in kWh = 3.16
Eimc in kWh = 0.61
Esdc in kWh = 0.19
Econ in kWh = 3.59
No. of charging = 0.32

Blue dots: single active power charging curves of synPRO-emobility
Solid line: average load of synPRO-emobility
Dotted line: average load with no. of charging per vehicle and day $\xi_d = 1.5378$ of Schäuble et al. (2017*b*, p. 262)
Dashed line: average load with no. of charging per vehicle and day drawn from the empirical distribution $\xi_d(100)$ of Schäuble et al. (2017*b*, p. 262)
No. of charging: calculated without intermediate charging

Figure 74: synPRO-emobility Simulation Results: Scenario 'P0' + Connection Indifference Levels in %-SOC: 50 (H), 50 (W), 80 (POP), 5 (SWE), Average Load of 100 BEV for 52 Weeks (364 Days), Aggregated and Distinct Charging Locations



Plot order (from above): aggregated load, H, W, POP-IC, POP-OC, SWE-IC, SWE-OC

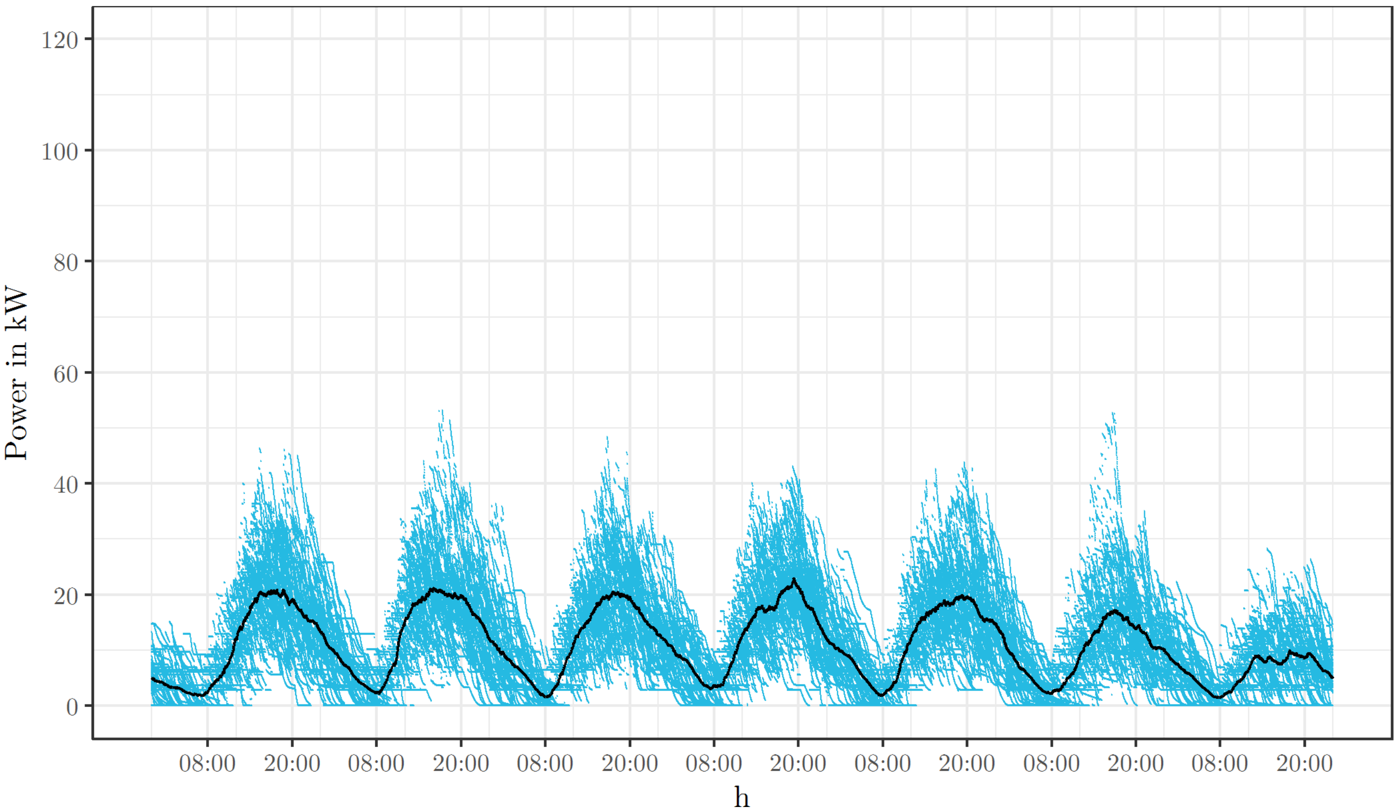
Blue dots: single active power charging curves of synPRO-emobility

Solid line: average load of synPRO-emobility

Dotted line: average load with no. of charging per vehicle and day $\xi_d = 1.5378$ of Schäuble et al. (2017*b*, p. 262)

Dashed line: average load with no. of charging per vehicle and day drawn from the empirical distribution $\xi_d(100)$ of Schäuble et al. (2017*b*, p. 262)

Figure 71: synPRO-emobility Simulation Results: Scenario ‘P0’ + Connection Indifference Levels in %-SOC: 50 (H), 50 (W), 20 (POP), 5 (SWE), Average Load of 100 BEV from 2Ay60p Households for 52 Weeks (364 Days), Charging Location (H)

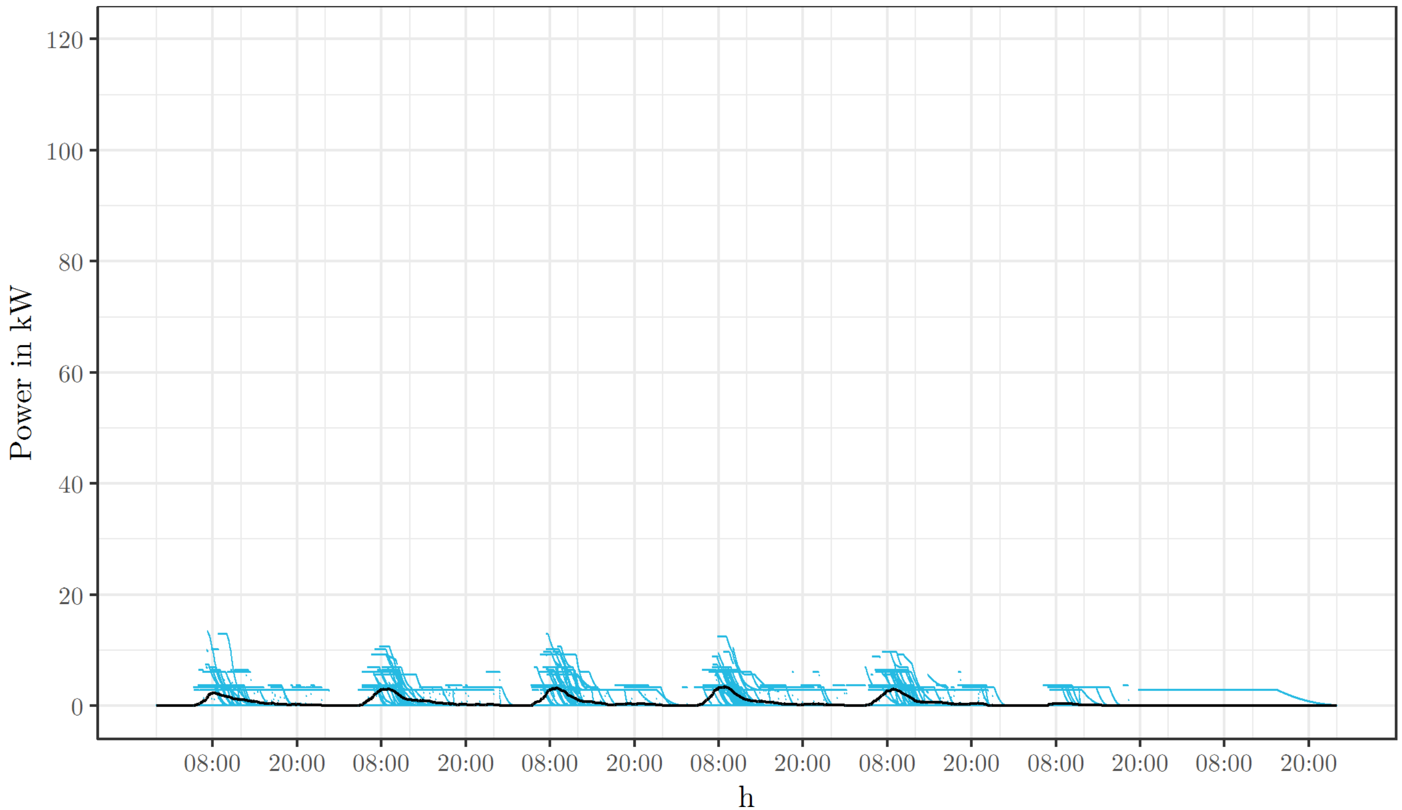


Total annual values
for 100 BEV:
Pmax in kW = 53
Ech in kWh = 94,971

Daily average per BEV:
Ech in kWh = 2.61

Blue dots: single active power charging curves of synPRO-emobility
Solid line: average load of synPRO-emobility
Dotted line: average load with no. of charging per vehicle and day $\xi_d = 1.5378$ of Schäuble et al. (2017*b*, p. 262)
Dashed line: average load with no. of charging per vehicle and day drawn from the empirical distribution $\xi_d(100)$ of Schäuble et al. (2017*b*, p. 262)
No. of charging: calculated without intermediate charging

Figure 72: synPRO-emobility Simulation Results: Scenario ‘P0’ + Connection Indifference Levels in %-SOC: 50 (H), 50 (W), 20 (POP), 5 (SWE), Average Load of 100 BEV from 2Ay60p Households for 52 Weeks (364 Days), Charging Location (W)

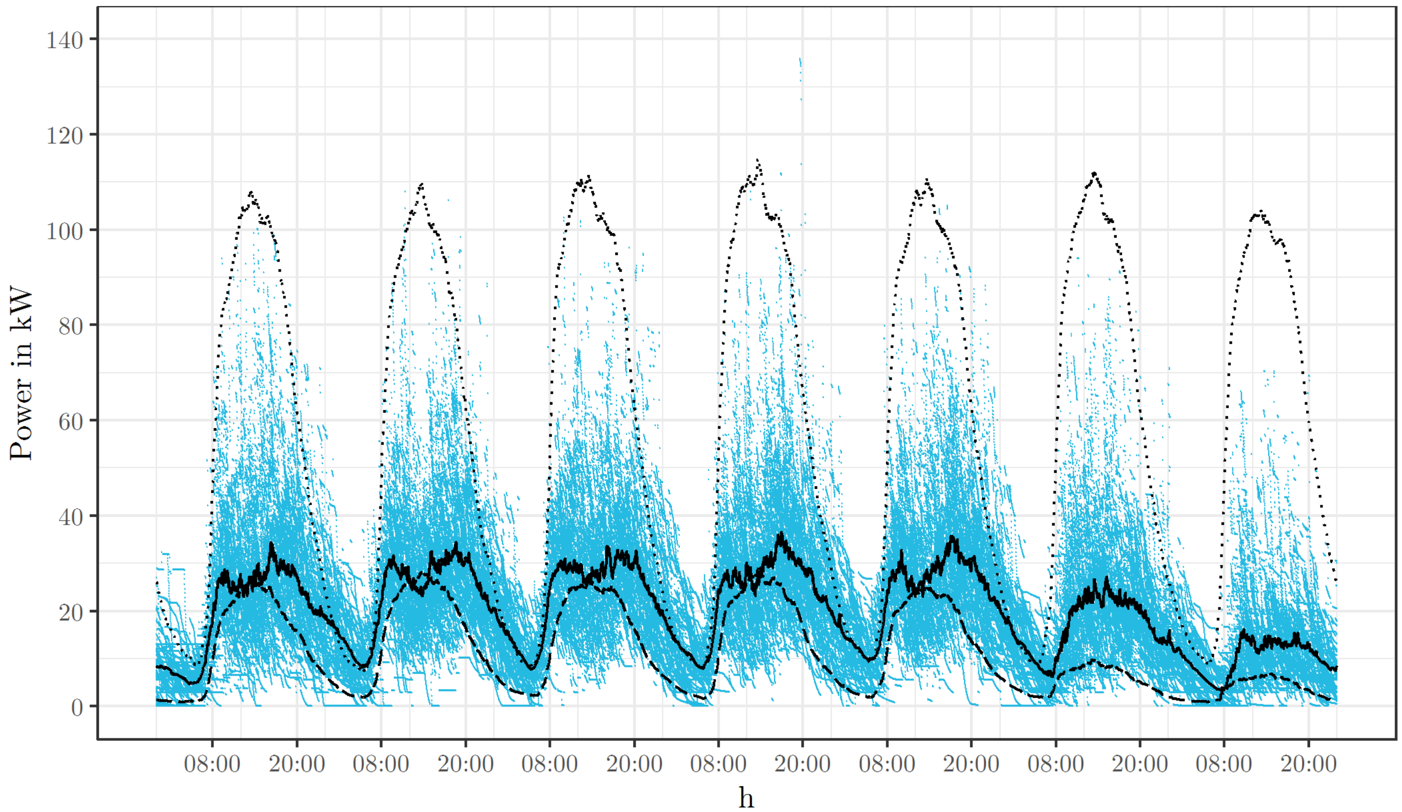


Total annual values
for 100 BEV:
Pmax in kW = 13
Ech in kWh = 4,809

Daily average per BEV:
Ech in kWh = 0.13

Blue dots: single active power charging curves of synPRO-emobility
Solid line: average load of synPRO-emobility
Dotted line: average load with no. of charging per vehicle and day $\xi_d = 1.5378$ of Schäuble et al. (2017*b*, p. 262)
Dashed line: average load with no. of charging per vehicle and day drawn from the empirical distribution $\xi_d(100)$ of Schäuble et al. (2017*b*, p. 262)
No. of charging: calculated without intermediate charging

Figure 73: synPRO-emobility Simulation Results: Scenario 'P0' + Connection Indifference Levels in %-SOC: 50 (H), 50 (W), 80 (POP), 5 (SWE), Average Load of 100 BEV for 52 Weeks (364 Days) Aggregated Over all Charging Locations

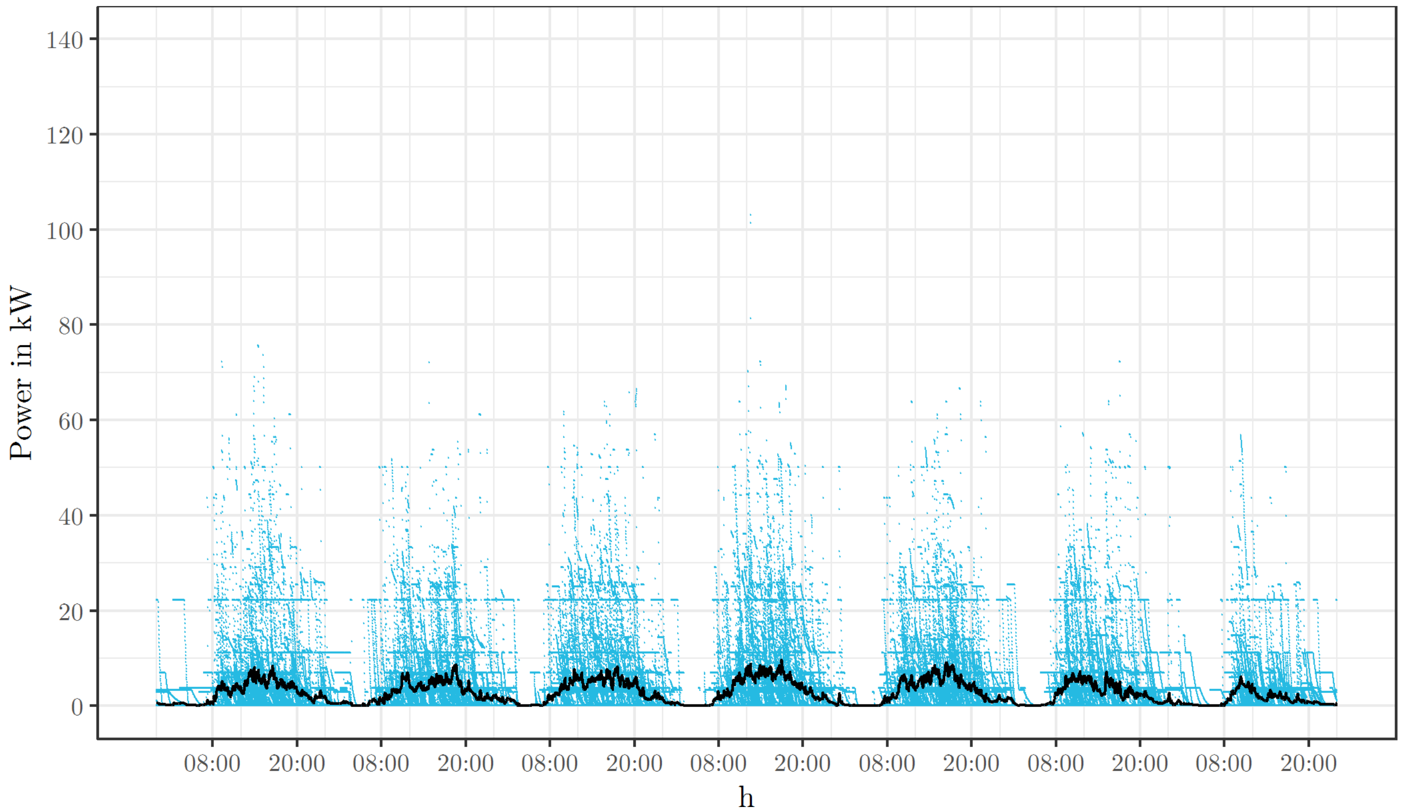


Total annual values
for 100 BEV:
Pmax in kW = 136
Ech in kWh = 174,214
Eimc in kWh = 19,150
Esdc in kWh = 10,042
Econ in kWh = 183,978
No. of charging = 19,319

Daily average per BEV:
Ech in kWh = 4.79
Eimc in kWh = 0.53
Esdc in kWh = 0.28
Econ in kWh = 5.05
No. of charging = 0.53

Blue dots: single active power charging curves of synPRO-emobility
Solid line: average load of synPRO-emobility
Dotted line: average load with no. of charging per vehicle and day $\xi_d = 1.5378$ of Schäuble et al. (2017*b*, p. 262)
Dashed line: average load with no. of charging per vehicle and day drawn from the empirical distribution $\xi_d(100)$ of Schäuble et al. (2017*b*, p. 262)
No. of charging: calculated without intermediate charging

Figure 75: synPRO-emobility Simulation Results: Scenario 'P0' + Connection Indifference Levels in %-SOC: 50 (H), 50 (W), 80 (POP), 5 (SWE), Average Load of 100 BEV for 52 Weeks (364 Days), Charging Location (POP-IC)

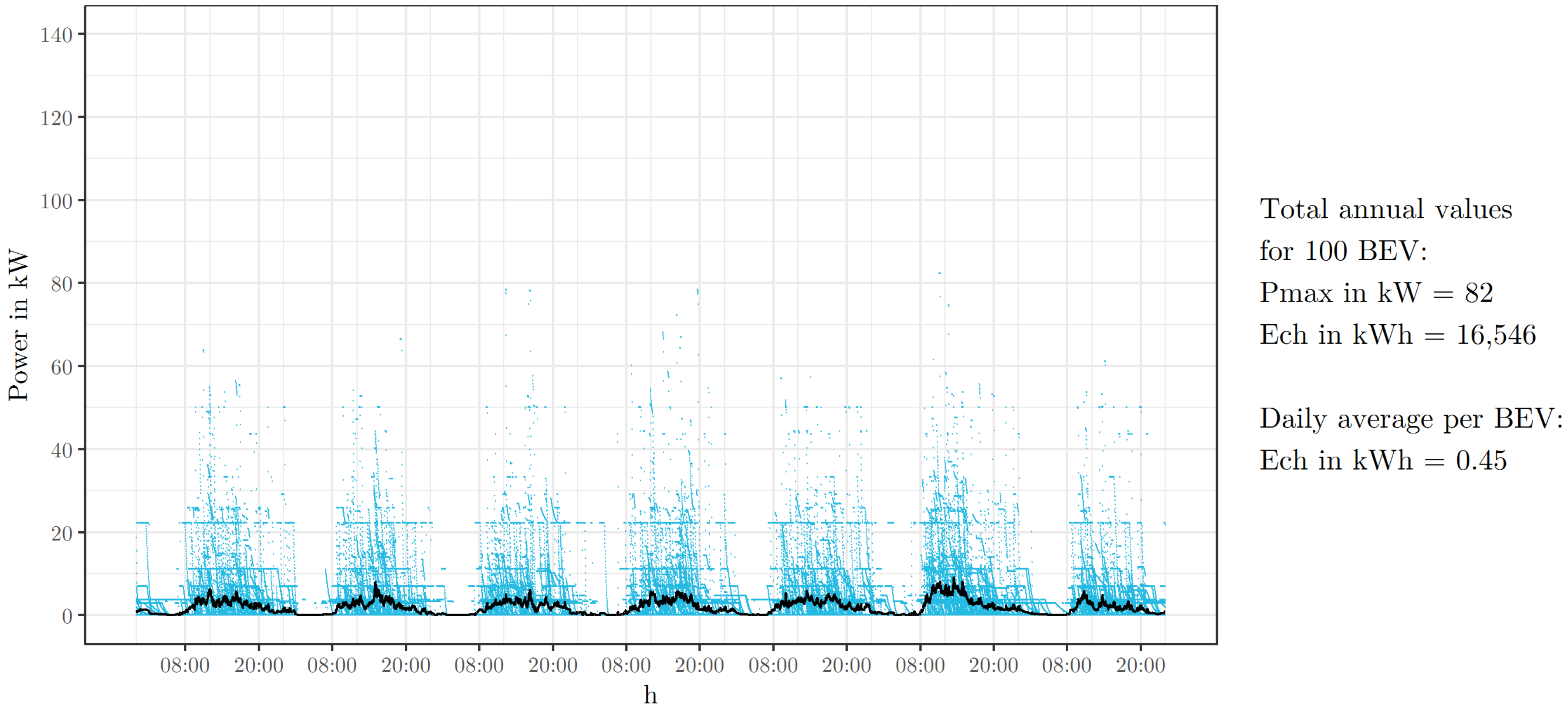


Total annual values
for 100 BEV:
Pmax in kW = 103
Ech in kWh = 23,204

Daily average per BEV:
Ech in kWh = 0.64

Blue dots: single active power charging curves of synPRO-emobility
Solid line: average load of synPRO-emobility
Dotted line: average load with no. of charging per vehicle and day $\xi_d = 1.5378$ of Schäuble et al. (2017*b*, p. 262)
Dashed line: average load with no. of charging per vehicle and day drawn from the empirical distribution $\xi_d(100)$ of Schäuble et al. (2017*b*, p. 262)
No. of charging: calculated without intermediate charging

Figure 76: synPRO-emobility Simulation Results: Scenario 'P0' + Connection Indifference Levels in %-SOC: 50 (H), 50 (W), 80 (POP), 5 (SWE), Average Load of 100 BEV for 52 Weeks (364 Days), Charging Location (POP-OC)



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No. of charging: calculated without intermediate charging

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