Thema *et al.*
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Drivers of car driving: lessons on infrastructure, peer-group, habits and socio-demographics from a survey on car ownership and usage in Germany

Johannes Thema[1,2*], Julian Reul[3], Marlin Arnz[4,5] and Frauke Wiese[2]

Abstract

Car ownership is the primary driver of car use, which in turn is the leading contributor to passenger transport sector emissions. Hence, understanding the key determinants of car ownership is crucial to designing a policy framework that will effectively reduce emissions. Based on a 2022 German mobility survey, this study utilizes multinomial logit models to analyse a range of influences on car ownership including socio-demographic and infrastructural factors, respondents' stated policy responses, and their motives for car ownership. We find that car ownership increases with an individual's age, income, the share of social contacts owning cars and with smaller towns of residence. Habits, measured as the number of years already spent as a car owner or non-owner emerges as a dominant factor. Our three main insights include: First, car ownership in rural Germany is particularly high and can be effectively reduced by public transport supply measures. Second, situations of radical change—when individuals overcome the force of routine to reflect on their car ownership status – present unique opportunities for policy intervention. And third, isolated or mild policy interventions may only have a limited impact. To significantly influence car ownership levels, policies will likely have to be very stringent.

Keywords Car ownership, Mobility survey, Multinomial logit model, Transport policy

*Correspondence:
Johannes Thema
johannes.thema@wupperinst.org
[1] Division Energy, Transport and Climate Policy, Wuppertal Institute for Climate, Environment and Energy, Doeppersberg 19, 42103 Wuppertal, NRW, Germany
[2] Department for Sustainable Energy Transition, Europa-Universität Flensburg, Auf dem Campus 1, 24943 Flensburg, SH, Germany
[3] Institute of Climate and Energy Systems - Juelich Systems Analysis (ICE-2), Forschungszentrum Jülich GmbH, Wilhelm-Johnen Straße, 52428 Jülich, NRW, Germany
[4] Workgroup for Infrastructure Policy, Technical University Berlin, Straße des 17. Juni 135, 10623 Berlin, Berlin, Germany
[5] Graduate School EnergieSystemWende, Reiner Lemoine Institut, Rudower Chaussee 12, 12489 Berlin, Berlin, Germany

1 Introduction

1.1 Context

Between 1990 and 2019, global final energy consumption in the transport sector jumped from 65 EJ to 120 EJ [1], causing transport CO_2 emissions to rise from 4.6 Gt/a (Gigatonnes/year) to 8.2 Gt/a [2]. This trend contradicts established targets for the reduction of global greenhouse gas (GHG) emissions. Also on a national scale, despite high reduction ambitions, transport emissions continue to rise in many countries. In Germany, the transport sector was the only sector for which CO_2 emissions rose (by 5%) between 1995 and 2020 [3]. The rise coincided with a steady growth in the number of private cars, which grew from 36.7 million to 49.1 million [4, 5], with the car manufacturing industry being one of the key industrial sectors employing about 780,000 people [6] and having major influence at European and national level [7]. The German transport sector consumes approximately 640 TWh/a (TWh/year) of final energy, with 2050 estimates of 189–635 TWh, depending on efficiency gains and vehicle kilometres (supplementary material of [8]). In combination with switching to renewable sources and efficiency gains, a reduction of car use is pivotal to reach significant reductions of climate emissions.

Since car ownership (CO) is the primary driver for car use, understanding the factors that influence ownership and creating policies to reduce CO are crucial to decarbonising transport. This article focuses on four aspects explaining change or stickiness of CO levels: transport infrastructures, social networks, routines and habits, and the role of life-course events, together with socio-economic and socio-demographic context. These have been previously studied, but only in separate analyses, we study them in a joint analysis.

The article is structured as follows: We first outline key relevant theory strands in Subsect. 1.2 and set our research focus in relation to the state of science Subsect. 1.3. Then, Sect. 2 describes our survey data and statistical analysis methods, Sect. 3 presents results of statistical analysis on car ownership drivers and assesses respondents' beliefs about the effectiveness of specific policies by examining their reactions to those policies. Following this, Sect. 4 discusses the relevance and reliability of our findings in relation to other literature and identifies issues for future research, especially with regard to modelling scenarios, Sect. 5 concludes the main findings.

1.2 Theoretical background

This section outlines the main theory strands on infrastructure, interpersonal norms, habits and life-course events.

According to the theory of planned behaviour [9], perceived behavioural control helps to understand the effect of framework conditions: if these do not allow for personal control, behaviour cannot follow intentions and framework conditions determine behaviour [10]. Other theories like the attitude-behaviour-context model [11] more explicitly focus on the role of constraints for individual action. When there are no external constraints, the attitude-behaviour link is strong. However, when framework conditions strongly impact action, the attitude-behaviour link is weak [12]. With regard to the analysis of car ownership, we can deduce that if context conditions do not allow for attitudes to determine CO decisions, they may directly drive individuals into CO. Good public transport conditions, for example, would allow for more attitude-based decisions and hence lower CO levels.

What others think or do may have impacts on personal behaviour and decisions. In 1759, Adam Smith wrote the first chapters of "The theory of moral sentiments" on sympathy and mutual sympathy [13], economic theory has set up respective utility functions that not only include personal interest but also utility of others [14]. Such effects have also been covered in social psychology within the theory of reasoned action [15] and varied in the theory of planned behaviour [9], where interpersonal norms (beliefs about what others think) influence subjective norms, the intention to act and final behaviour. Following these lines, the observation of (no) car ownership in the peer group can thus be expected to influence personal decisions.

Triandis' theory of interpersonal behaviour [16] synthesises other theoretical frameworks [12] to cover attitudes, contextual factors, personal capabilities and also habits. Habits are understood as the frequency of past behaviours. Ølander and Thøgersen [17] proposed a motivation-opportunity-ability (MOA) model that understands habits as independently determining behaviour, but also as moderating subjective intentions. From this perspective, the more behaviour becomes a habit with daily routine, the less likely become alternative decisions.

Habit formation can be understood to happen in 3 stages [18]: (1) declaration: information processing, decision-making; (2) knowledge compilation: converting decisions into new routine, positive feedback process if new routine functions well; (3) procedural stage: lock-in into new habit without further reflection on action. Habits can be expected [19] to be stronger, the more frequently repeated and the more frequent positive reinforcements (experiences and feedback) are received. Jackson [12] elaborates on how habits may be broken. One reason for breaking habits may be life-course events that lead to an "unfreezing" of habits [20]. Harms et al. [10] additionally argue that relevant contextual changes are not necessarily single events, but may be cumulative and even anticipated changes.

The complex initial decision to own a car involves previously discussed mechanisms. Once taken, it leads to certain mobility patterns with routines of car use that will then perpetuate the CO state. A change ("unfreezing") of habits becomes increasingly unlikely over time.

1.3 Empirical findings for car ownership determinants under study

Infrastructure and framework conditions: Accessibility and proximity to public transport has been analysed by a large number of CO studies [21–29]. Research suggests that developing compact cities, improving public transport [29] and increasing accessibility [23], i.e. a "walking" instead of "automobile urban fabric" [30] would support lower CO levels. Urbanisation or population density is a common proxy for lower CO [31].

Improving cycling infrastructure that promotes separate lanes, visible crossings, traffic calming, secure stationing, PT integration, training and education for cycling has also been found conducive to lower CO levels [29, 32], as has the ”urban form” with transit accessibility, cycle lane share and distance to city centres [33].

[29] find that with improving public infrastructures for pedestrians, cyclists and public transport while tightening car use policies to make driving slower, less convenient and more costly during the past 25 years, the five largest cities in Germany, Austria and Switzerland have significantly reduced car use. However, due to the macro-level nature of the study, no single policy can be evaluated.

Social network effects: The literature body on peer group effects on car ownership is limited. A review study [34] finds that “the stronger someone considers that buying and car and travelling by car is the normal and expected thing to do, the higher the chance that they do it”. For the case of New York and based on old (1997) data, [35] find a higher probability of car-ownership if households are surrounded by other car-owning households. An analysis of only student car ownership differentiates various peer groups and finds only significant influence of siblings [36].

Habits and life-course events: Past decisions have been found to be the best predictors of current ones. Observing a strong auto-correlation in panel data, several studies [37–40] note that the variance of one observation over time is much lower than that between observations. This suggests that established habits and unobserved heterogeneity (i.e. explanatory factors that are not included in available data and can thus not be estimated) are highly relevant.

Studies have also analysed influences of life-course events, that arguably may not only be single events, but cumulative and even anticipated [10, 41], initiating a large evolving literature strand. As events that are key for influencing CO decisions have been identified a change in number of adults per household, the birth of a first child, a change in household income and mixed results on residential relocation [42].

Socio-economic and demographic context: Empirical studies typically include a number of socio-demographic and economic control variables, for some studies these factors are the core interest [30]. Income has been found largely positively correlated with CO, and several studies [22, 31, 43–47] confirm the finding [48] that CO persists even when income falls.

Consistent with [42], the presence of children, increasing age and number of driving licences in the household have been found largely positively correlated with CO [43, 49, 50]. Differentiated socio-demographic analysis found a decline in CO among young German men aged 18–29 (eliminating the gender gap) [50], and of young adults aged 18–34 [51], possibly because of the younger generation’s increased sensitivity to policy and cost changes. Socio-demographics and geographic explanations are studied by Oakil et al. [31] with similar findings.

1.4 Approach of this study

Previous studies have found the mentioned factors as important, but have only focused on one or two of them, controlling for socio-demographics. Our contribution to the field is the joint analysis of infrastructure, interpersonal and habit effects and how these relate to standard socio-demographic effects. For this, we combine three methodological approaches: we use cross-classification for descriptive socio-demographic analysis, estimate a discrete choice model, and complement findings with plots of expected policy responses to analyse respondent’s stated reactions to policies.

This allows us to test the following hypotheses based on the above theory and findings in literature:

- Good public transport conditions lead to lower levels of CO.
- High share of CO in one’s peer group increases the likelihood of personal CO and number of cars.
- The longer a (non) CO situation persists and thus becomes a habit, the less likely a change.
- In order for policies, i.e. changes to framework conditions to be effective, they need to be strong.

The analysis relies on open data from a recent German cross-sectional mobility survey. As no panel data is used, over-time effects (life-course events) cannot be analysed, but consistency of our findings with panel data study findings is assessed.

2 Material and methods

This section outlines the survey data analysed in the study and our analytical approaches, including cross-classification descriptive statistics of car ownership, multinomial logit models to identify the factors driving car ownership, and an analysis of how car-owning survey respondents state to react to potential future policy measures.

2.1 The TRA-DE mobility survey

Our analysis is based on the German TRA-DE survey conducted between January and May 2022, yielding N=3422 observations, gathered for three urbanisation categories (population of residence place: small = 5,000–19,999, medium = 20,000–99,999 and large =

over 100,000 inhabitants). Responses were more or less equally distributed across all three classifications. The survey data was obtained from online access panels (OAPs), with representative sampling quotations. While weights were generated to ensure representativeness in terms of socio-demographics (age, gender, education), the weighting did not consider the population density of respondents' differing residential areas. Consequently, urban respondents are slightly overrepresented. A comparison against official statistics by Destatis [52] can be found in Figure 60 of the supplementary material. The original survey questionnaire, the survey method report, data codebook, and dataset are published under an open license at Zenodo [53].

Our questionnaire is loosely based on the large German transport survey *Mobility in Germany* (MiD) [54], complemented by items based on the research findings discussed in Sect. 1. The questionnaire consists mainly of closed questions, with some options for open responses. The main sections cover: (1) Mobility equipment and use details, (2) Trip purposes, length and modes, (3) Reasons for choices, mobility restrictions (4) Policies, subdivided into (a) Desired changes and (b) Plans of respondents to reduce car use or to abandon the use of cars altogether, in response to known and researched policies, along with a (5) section on peer groups and a 6) standard block of socio-demographics.

We use data on the following variables: number of cars per household, socio-economic and geographic indicators on employment/the workplace, proportion of CO in one's peer group, length of time as car owner/non-owner, reasons for car ownership decisions, and stated responses to specific policy measures. These variables and their source codes are listed in Table 1. Summary statistics of the variables analysed in the models are provided in Table 2.

2.2 Cross-classification analysis of car ownership

To address the research question "Who owns a car and why?", we first provide descriptive graphical analyses of key items. This includes a cross-classification analysis of the number of household cars vis-a-vis respondents' income, age, gender, and hometown size; and analyse their stated reasons for owning a car. To ensure that the results are representative of the German demographic distribution for age, gender, and education, we use appropriate structural weights for all statistics and figures. Data processing, analysis and graphical representation are provided as a python script (jupyter notebook) and as a separate document with graph outputs in the supplementary material.

Table 1 Items used in the analysis

Variable	Description	Source var. in dataset
Cross-classification and MNL model		
Nr of cars	Number of cars available in household	F1-1A1
Age	9 age classes (10-year steps)	F26
Nr of persons	Total number of persons in household	F29A1 to -4
Nr of persons <18y	Number of persons <18 yrs in household	F29A2 to -4
Nr of persons ≥18y	Number of persons >18 yrs in household	F29A1
Health limitations	Person reporting health problems or disability	FH.1A1
Income	6 income classes (<1500€, 1000€-steps)	F31
Employed	Full or part-time employed	F28
Work distance (log)	Km travelled to workplace in an average week (km logarithmic)	arbeit.F
Work from home	Working one or more days from home	F5
Pop. size	3 classes of residence population size (5-20k; 20k-100k; >100k)	ewzahl
Dist. to provisioning	Radius within which most daily needs can be met (shopping, medics, leisure)	F7A1
Poor PT quality	Poor quality of public transport and cycling infrastructure reported as reasons for CO	FA.2A2
CO in peer group	Share of friends owning a car (10% steps)	F23A1
Years with no car	Years respondent does not own a car (<2, 2-10, 10-year steps)	FB.2
Years with car	Years respondent owns a car (<2, 2-10, 10-year steps)	FA.4
Additional items analysed		
Reasons for CO	Stated reasons for owning a car (12 items)	FA.1A1 to -12
Reasons for no CO	Stated reasons for not owning a car (10 items)	FB.1A1 to -10
React to cost factors	Stated reaction to car-related cost factors (7 items)	F12a1-2 to F12i1-2
Prob react to policy	Stated probability of reacting to policies (8 items)	F14a1-2 to F14k1-2

Table 2 Summary statistics of model variables

Variable	Min	Max	Mean		Std		Median	Comment
			Non-weighted	Weighted	Non-weighted	Weighted	Non-weighted	
Work distance (week^{-1}, log)	0	8.006	3.980	3.950	1.364	1.371	4.094	No max set
Work distance (week^{-1})	0	3000	116.417	112.844	180.562	168.863	60	No max set
Work from home	0	1	0.383	0.341	0.486	0.474	0	Employed persons
Dist. To provisioning	0	20	7.548	7.307	4.904	4.894	6	
Health limitations	0	1	0.079	0.114	0.269	0.318	0	
CO in peer group	0	10	7.237	7.322	2.845	2.913	8	
Age	1	8	n.a.*	n.a.*	n.a.*	n.a.*	4	
Employed	0	1	0.605	0.500	0.489	0.500	1	Full/part-time
Nr of persons	1	10	2.053	1.965	1.036	0.969	2	Limited to max 10
Nr of persons <18	0	10	0.675	0.519	1.323	1.192	0	Limited to max 10
Nr of persons ≥18	1	20	2.728	2.483	1.944	1.787	2	
Income	1	6	2.944	2.769	1.456	1.445	3	
Poor PT quality	0	1	0.579	0.558	0.494	0.497	1	Based on hh with cars
Years with no car	0	7	n.a.*	n.a.*	n.a.*	n.a.*	0	Based on all hh
Years with car	0	6	n.a.*	n.a.*	n.a.*	n.a.*	2	Based on all hh
Nr of cars	0	10	1.161	1.090	0.924	0.863	1	

*Variable categorical or with varying class sizes, therefore mean/std calculation not meaningful

2.3 Discrete choice analysis

Discrete choice and random utility theory is designed to analyse individual decisions between discrete alternatives (e.g. owning a car or not). It is commonly applied through multinomial logit (MNL) models, which are especially useful for their rich theoretical background and analytical mathematical formulation [55]. Random utility theory derives such models from economic theories of rational choice and individual utility maximisation, while including non-rational factors through probabilistic elements calibrated to survey data. MNL models have been developed for transport studies in the 1980s [56], have been continuously developed, and are still the most common method in transport studies [55, 57, 58], and specifically in CO research [44]. Potoglou and Susilo [49] show that MNL models are a more appropriate methodological framework for CO modelling than ordered logit or probit models.

We use the open source framework MO DE.behave for MNL model estimation, which is available on GitHub [59] and published in [60]. In MNL models, the probability of choosing one discrete alternative $L_i(\beta)$, dependent on attribute weights β is expressed as:

$$L_i(\beta) = \frac{e^{V_j(\beta)}}{\sum_{j=1}^{J} e^{V_j(\beta)}} \tag{1}$$

with the linear function $V_i(\beta)$ giving the observed utility for each choice option i. We model four discrete choice alternatives: (0) zero cars, (1) one car, (2) two cars and (3) three or more cars. For this study, we use the following terminology. *Attribute* denotes explanatory factors (e.g. income) that are independent of the alternative choice options. When such an attribute is associated with a specific choice (for example, when income is associated with the choice alternative "0"), this is termed *variable*. Estimators resulting from the model are termed *parameters*.

MO DE.behave provides further post-processing routines to calculate the summary statistics for the multinomial logit models estimated in this study, including log-likelihood-ratio (LL-ratio), Akaike, and Bayesian Information Criterion (AIC and BIC).

We specify three models to test for the robustness of our estimated parameters. In selecting model attributes for the default model, we drew on those found in other studies we reviewed (Sect. 1), covering socio-demographics, infrastructure-related variables and ownership in the peer group as proxy for interpersonal norms. These attributes were further refined in an iterative process, taking into account an evaluation of the summary statistics (LLR, AIC, BIC). We present three models with parameter estimates and summary statistics for each model specification. For the four defined choice options (0, 1, 2, 3+ cars), the 'default' model is given 55 parameters consisting of three alternative-specific constants and 52 variable parameter estimators that describe the respondents' preferences for each of the 13 attributes. For each attribute, we estimate four parameters corresponding to each of the four choice alternatives. The alternative-specific constant for the choice option of zero cars is normalised to zero.

We then test the robustness of the 'default' model parameters to a number of changes. Here, we exclude variables of lesser significance, merge attribute details (nr of people instead of separated by age) and exclude variables (employment), also associated with the quality of the public transport and cycling infrastructures. The aim of the latter exclusion is to test for an endogeneity problem, given that the data for this variable was obtained exclusively from car owners. This 'sparse' model also combines into one variable respondents from two separate age groups (under and over age 18) and excludes two minor work-related attributes in the default model.

The third 'routine' model adds to the default model two variables (years as a car owner/non-owner) to test the impact of past action on the current situation. These are then the only time-related variables in the model.

2.4 Analysis of stated reactions to policy measures

As a final step, to assess potential policy impacts we outline respondents' stated reactions to specific policies. Here, we classify respondents' assertions that they would "reduce car use to 1–2 times/week" or "entirely scrap" their car in response to specific policies. Responses are arranged in order of policy stringency and the respondent's stated likelihood to follow through with the stated reaction. This yields a cumulative stacked bar chart (for policy stringency) and cumulative distribution function (for stated probabilities of following through with the stated reaction).

3 Results

3.1 Car ownership by socio-demographic factors

The German *TRA-DE* survey data covers most of the explanatory factors encountered in the literature (Subsect. 1.3). Descriptive statistics as cross-classifications of car ownership by hometown population size, gender, income, and age (see Fig. 1) show that the proportion of households with one car increases with age. Thus, proportionately more respondents under 29 years old report that they own no car or live in two- and three-car households. This is probably due to a correlation with household size, which studies have deemed significant for CO. Multivariate analyses are presented in the following section. Consistent with the literature, income seems to be a key explanatory factor for CO (that is, the number of cars increases with rising income). Relative to men, a higher share of women report that they have no car and a lower share report that they have one car. However, ownership of two or more cars remains consistent across both genders. Relative to those of other genders, a higher share of people who gender-identify as "diverse" report having either no car at all or 3 cars; however, this is only based on 16 observations and may be correlated with variables such as age or income. The share of respondents without a car is significantly higher in larger cities, especially those with >100,000 inhabitants, while the share of respondents with two or more cars decreases inversely. The proportion of single-car owners remains fairly consistent across all city sizes.

The main reported reasons (>80% positive response) for owning a car include comfort and reliability, the accessibility of destinations, the convenience of transporting things, and a feeling of freedom and

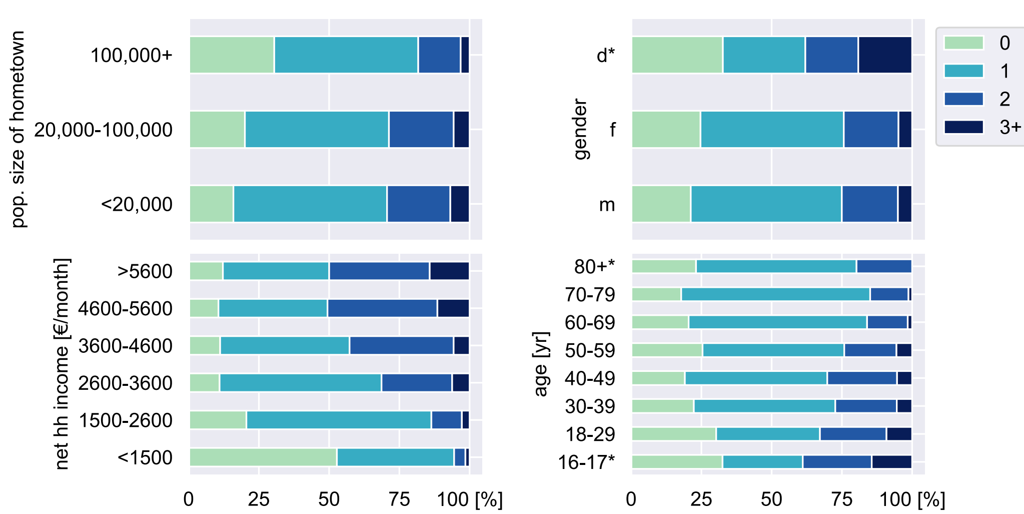

Fig. 1 Number of cars per household, by population size of hometown, gender, income, age. **Note*: d=diverse based on N=16 observations, age class 80+ on N=8, age class 16–17 on N=63

self-determined mobility. Other reasons include low costs, the need to accompany other people, commuting needs, and inadequate public transport alternatives. Fewer respondents (>50%) report having a car as “standard” or “normal with friends” and infection prevention in the context of the Covid-19 pandemic as reasons for CO (see Fig. 2). These findings are consistent with those of other studies, while infection prevention was a new issue at the time of its emergence. The stated reasons are also relatively stable across age, income, and hometown population size. Some reasons, however, deviate across these dimensions (for specific figures, see Figs. 4 and 5 in the supplementary material). In particular, poor PT accessibility and commuting issues appear to have a greater impact in less populated areas. Relative to other respondents, those aged >60 report fewer reasons related to social norms (“normal with friends”, “it’s just standard”), the need to give other people a lift (“accompany”), or commuting issues. Infection prevention remains important across all groups (Note: data collection early 2022).

Most (over 50%) of the carless respondents cite high running and acquisition costs, environmental considerations, and the fact that they “do not need” a car as their reasons for not owning one (see Fig. 2b). Structurally, the share of persons who name these reasons is much higher in urban than in rural areas. A larger fraction of respondents under the age of 30 report “not having a driving license”; other reasons are less pronounced. When considering income as a parameter, significantly higher fractions of carless respondents with high incomes cite all reasons except not having a driver’s license and the role of car acquisition costs. Cross-classification analyses that support these findings are included in the supplementary material (Figs. 16, 17, 22).

3.2 Statistical analysis of reasons for car ownership

This section uses discrete choice theory to further analyse the factors that influence CO in private households. We estimate MNL models using the framework MO DE. behave to describe the car ownership choices of private households with respect to the number of cars owned.

The ‘default’ model specification covers 12 attributes. The ‘sparse’ model combines two and omits three of the these (total: 8) whereas the ‘routine’ model tests two additional attributes (total: 14), which indicate the years of previous CO/non-CO to analyse the explanatory power of past CO status on a subject’s observed CO status. Model specifications and estimations are displayed in Table 3.

3.2.1 ‘Default’ model results

Results from the ‘default’ model are consistent with the cross-classification results and with findings reviewed in Sect. 1. Figure 3 graphically presents ‘default’ model results. For each attribute, parameter values for the four choice options are shown. The bars indicate parameter values for every variable category. Consequently, a dichotomous variable shows only one bar stack, while variables with n categories show n-1 bar stacks.

The figure shows that, despite the statistical significance of many parameters, the importance of attributes varies strongly. The model is dominated by the attribute *quality of PT and cycling infrastructure*, followed by *number of persons above 18y*, *health limitations*, *income*, *age*, *population size of hometown*. This section discusses ‘default’ model results in detail.

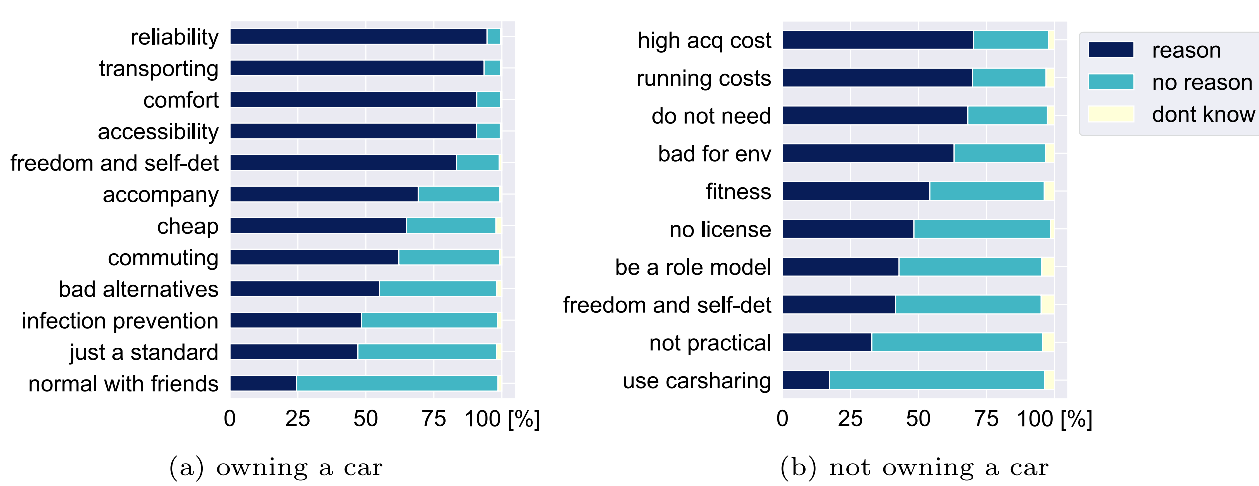

Fig. 2 Reasons stated for owning a car (**a**) and not owning a car (**b**). For details on questions and items see questionnaire and codebook at [53]

Table 3 MNL model specifications and results

Model	**Default**				**Sparse**				**Routine**			
Number of Cars	**0**	**1**	**2**	**3+**	**0**	**1**	**2**	**3+**	**0**	**1**	**2**	**3+**
ASC	Reference	− 4.397***	− 7.284***	− 8.227***	Reference	− 3.147***	− 5.805***	− 6.827***	Reference	2.761***	− 0.534	− 2.346***
Work distance (week^{-1}, log)	− 0.092***	0.031	0.127	− 0.067*	− 0.108***	0.035*	0.099***	− 0.025	− 0.056	0.015	0.139*	− 0.098
Work from home	0.429	0.121	− 0.151	− 0.399					0.148	0.15	− 0.062	− 0.236
Dist. to provisioning	− 0.077***	0.022	0.033	0.023	− 0.093***	0.022	0.039***	0.032***	− 0.016	− 0.004	0.01	0.01
Health limitations	0.781***	0.731***	0.822	− 2.334***	0.659***	0.771***	0.795**	− 2.226***	0.041	0.628***	0.763	− 1.431***
CO in peer group	− 0.282***	0.015	0.158***	0.108*	− 0.284***	− 0.006	0.15***	0.14***	− 0.07	− 0.058	0.083	0.046
Age	− 0.031	0.224***	− 0.012	− 0.181**	− 0.05	0.195***	0.0	− 0.145*	0.247***	0.171***	− 0.127*	− 0.291***
Employed	− 0.088*	− 0.076	− 0.185	0.348					− 0.045	− 0.104	− 0.324	0.473
Nr of persons					− 0.346***	− 0.087***	0.154***	0.28***				
Nr of persons <18	− 0.098	0.018	0.06	0.02					0.091	− 0.047	0.005	− 0.049
Nr of persons ≥18	− 0.697***	− 0.278***	0.3	0.675***					− 0.354***	− 0.471**	0.19	0.635**
Population size	0.416***	0.214***	− 0.118	− 0.512***	0.454***	0.129***	− 0.173**	− 0.41***	0.321***	0.191	− 0.111	− 0.401
Poor PT quality	− 12.533***	3.961***	4.155***	4.417***					− 0.849***	0.069	0.257	0.523
Income	− 0.426***	− 0.199***	0.214***	0.412***	− 0.449***	− 0.187***	0.225***	0.412***	− 0.004*	− 0.347***	0.077**	0.274***
Years with no car									4.901***	− 2.686***	− 1.448***	− 0.767***
Years with car									− 3.853***	1.21***	1.306***	1.336***
LL_RATIO	0.454				0.367				0.651			
LL_FINAL	− 2034				− 2359				− 1301			
AIC	4170				4788				2720			
BIC	4469				4993				3066			

Significance code: *** 0.01, ** 0.05, * 0.10

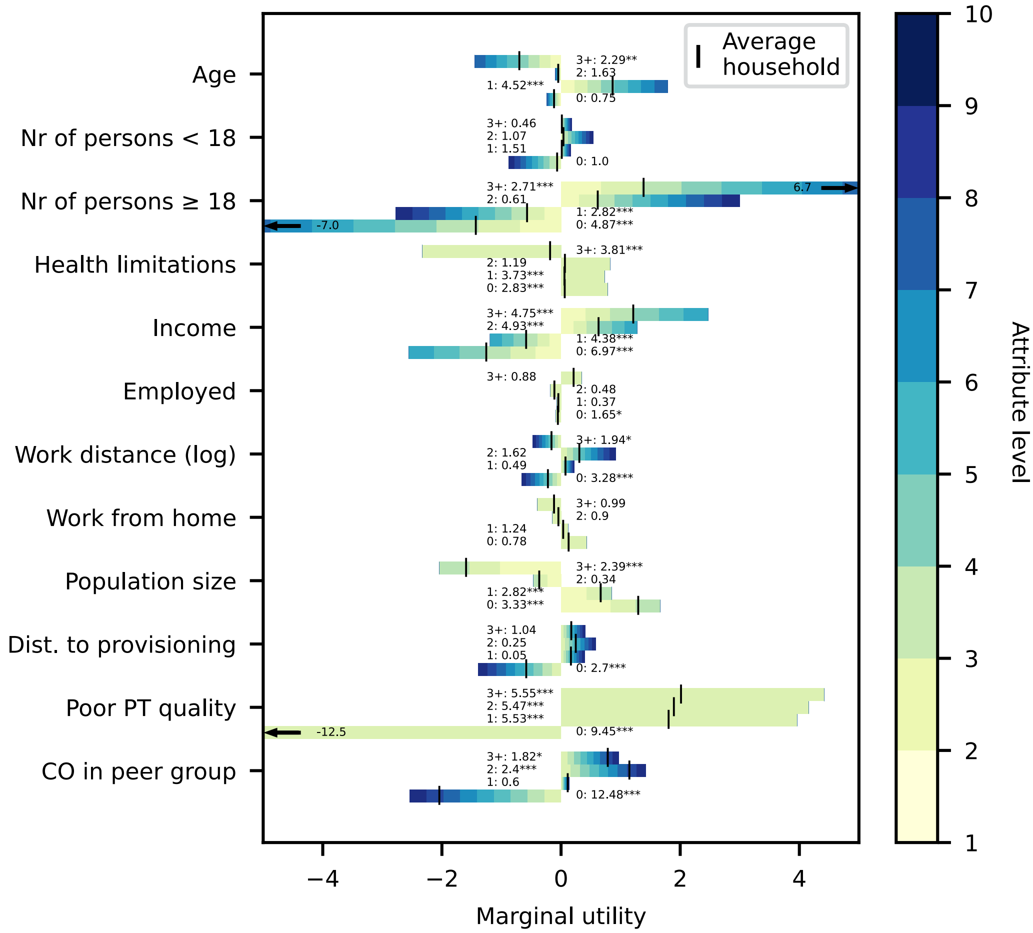

Fig. 3 Overview on parameter estimates in the 'default' model: influence of variable values on utility of choice options. *Note*: Choice options denoted with [0, 3+], followed by t-statistic with significance stars (significance code: *** 0.01, ** 0.05, * 0.10) The number of attribute levels displayed per choice option depends on number of categories in the respective attribute

The model is largely driven by infrastructure and socio-geography. Households that cite poor public transport and cycling infrastructure as a reason for owning a car are significantly less likely to live without one and much more likely to own one or more vehicles. This is the dominant explanatory factor in the model and supports our first research hypothesis. As already found in the cross-classification, households in large cities forego car ownership significantly more often and choose to own three or more cars significantly less often than other households. This effect of city size is relatively strong and additional to transport infrastructure. A third related effect concerns distance to vital services: the greater this *distance to provisioning*, the less likely it is that a household will have zero cars. However, this is a minor effect.

Socio-demographic and individual attributes are also important. In this model, the number of household members aged under 18 is not significant, the number of children in a household does not increase the likeliness of CO. A significant effect is observed for the number of adult persons as the second-largest parameter value (see parameter values and significance in Table 3 and Fig. 3), with the number of cars increasing as the number of potential drivers goes up. The probability of owning one car increases with age, although older people are less likely to own three or more cars. Respondents who report health problems are more likely to own no or one car, and are less likely to own three or more cars.

The probability that a household will own two or more cars increases with household income, reducing the probability of not owning any car. Employment status measured separately from income does not have an additional significant effect. The (log) distance to workplace is found to be very small, and only statistically significant for the options of not owning a car and owning 3+ cars, reducing both probabilities. In our models, the isolated effect of working at least one day from home office is not statistically significant for explaining CO.

Finally, the social environment has a strong effect on an individual's CO decisions. Relative to other groups, people whose friends and family include a greater share of car owners are more likely to opt for two or more cars and less likely to go carless. This hints at the potentially high relevance of social norms and supports our second research hypothesis.

3.2.2 'Sparse' model results

The 'sparse' model specification excludes and merges several attributes of the 'default' model, as explained in the methods section. In response to these model modifications, the values of the parameters, and in some cases their significance, are altered, but the signs of the parameters as well as their explanatory patterns remain stable. Figure 1 in the supplementary material shows graphical outputs for pattern stability compared to Fig. 3.

First and most important is the omission of the parameter that dominates the 'default' model (PT and cycling infrastructure quality), as we test the estimator stability even for the case that endogeneity with this variable exists. We find that significance and size of parameters remain relatively stable between both models, and that utility values are proportionately lower. The omission of the *Poor PT quality* attribute only marginally alters the effects of *population size* and *distance to provisioning*. The largest parameter values are found for *income* and *number of persons*. This merged variable picks up the significant impacts of the *number of persons above 18y* in the 'default' model. Logged work distance as the only remaining work-related attribute apparently picks up only little of the variance of the omitted work-related attributes. Here, impacts remain stable relative to the 'default' model.

The LL-ratio decreases from 0.454 in the 'default' model to 0.367 in the 'sparse' model, AIC and BIC values increase for the 'sparse' model. The finding that attribute omission changes little with respect to parameters but decreases the goodness of the fit suggests that the less parsimonious 'default' specification should be preferred over the 'sparse' model.

3.2.3 'Routine' model results

The 'routine' model specification extends the 'default' model by two attributes: *years with car* and *years with no car*, which measure the number of years that a given household has maintained its current CO status (in six categories; see Table 1). This attribute is intended to measure routine and habit [12], and likely also captures other influences not explicitly surveyed (unobserved heterogeneity). In accordance with the literature (Sect. 1.3), past behaviour is typically the best predictor of current behaviour, and both attributes are highly significant (as expected; see parameters of *years with (no) car* in the 'routine' model in Table 3), and exhibit an almost inverse relationship. Figure 4 shows that the two routine attributes outvalue by orders of magnitude other parameter values that remain at similar levels of previous models. The longer a household owns a car, the less likely it is to go carless - and the more likely it is to acquire more cars. Conversely, the probability of remaining carless rises as the number of carless years increases. We also observe a negative correlation between such a routine with the choice alternative to acquire one or more cars, indicating that the likelihood of changing one's car ownership status decreases over time. These results are consistent with the literature [37–39] and suggest that routines and habits have a very strong impact on car ownership decisions, especially regarding whether to own several or only one car. In a situation where 78% of households own at least one car, the total number of cars is expected to rise, consistent with the empirical observation in Germany.

The introduction of the two variables in the 'routine' model increases the LL-ratio to 0.651, while AIC and BIC fall far below the values of the 'default' model. This indicates the high explanatory power of the additional attributes. While most of the other parameters remain stable, at least in general patterns, the routine introduction brings several changes to the significance and values of the estimated parameters relative to the default model that we highlight here.

In this model specification, increasing age is associated with a higher likelihood of not owning a car. Controlling for the routine/habit effect and for underaged persons, the isolated age effect would seem to yield a higher tendency towards carlessness. This indicates that the amount of time spent (not) owning a car, rather than the age itself as suggested by the 'default' model, largely drives the CO effect. By contrast, the likeliness of not owning a car increases with increasing age (and parallel non-ownership status). However, this is heavily outweighed by the routine effect. Relative to the default model, health limitation effects remain stable but decrease slightly, whereas the effect of employment becomes insignificant, the income effect remains stable, with one important alteration: Income has no significant influence on the decision to not own a car (households may forcedly or voluntarily not own a car with low and with high incomes), but it remains a significantly positive and important factor underlying the choice of how many cars to own. The probability that a person will choose to own one car decreases as distance to the workplace increases, although at a very different level of the alternative-specific constant. Working from home lowers the probability that one will go carless, but the impact size is marginal and statistically insignificant.

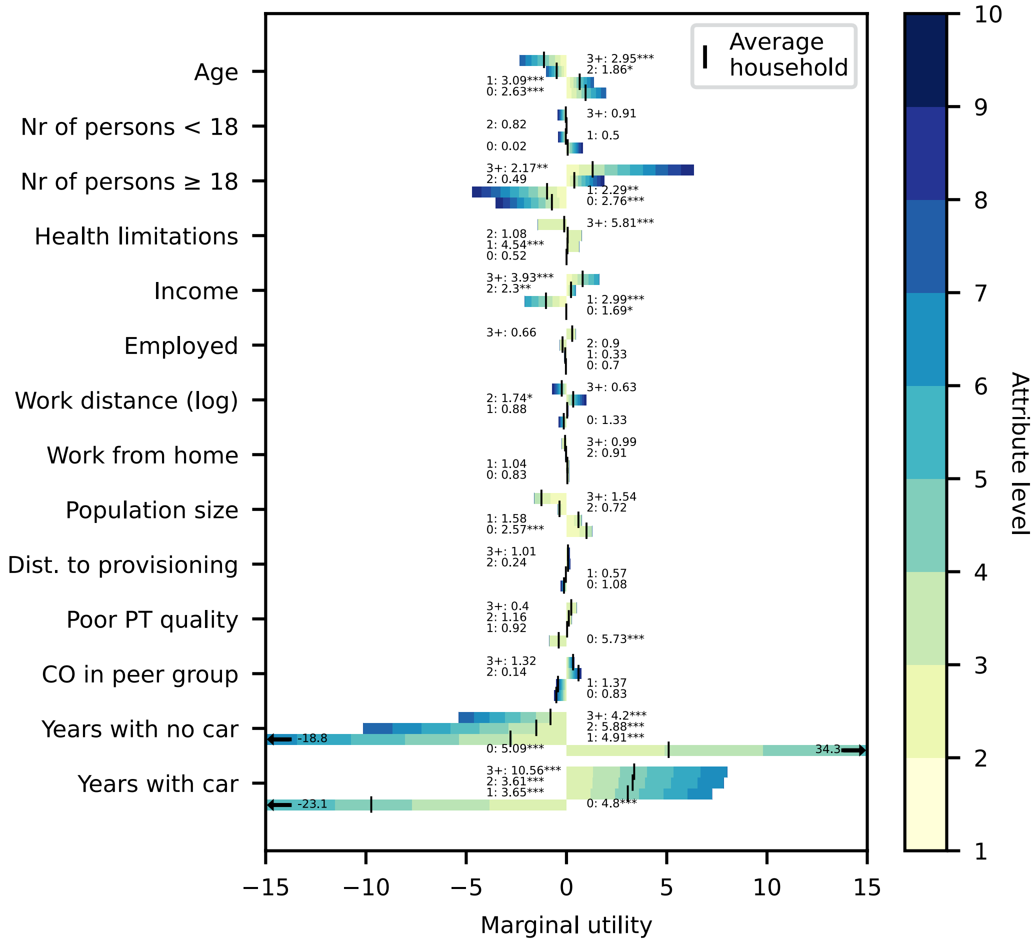

Fig. 4 Overview on parameter estimates in the 'routine' model: influence of variable values on utility of choice options. *Note*: Choice options denoted with [0, 3+], followed by t-statistic with significance stars (significance code: *** 0.01, ** 0.05, * 0.10) The number of attribute levels displayed per choice option depends on number of categories in the respective attribute

The quality of the public transport and cycling infrastructures - previously highly important - maintain their expected effect on the probability of going carless, but with lower effect sizes. Finally, the effect of social influences is rendered insignificant.

Introducing the routine/habit variables thus improves the goodness of the fit, but also picks up variance from other variables, especially from age, infrastructure quality and peer group effects. This is certainly due to some degree of multicollinearity: Relative to younger ones, older respondents have spent more years owning/not owning a car. Likewise, when infrastructures have influenced decisions in the past, most likely they will continue to do so today and are inscribed in a person's habits. The assumption is that social surrounding probably does not vary much over time, and specific effects are picked up by the routine/habit variables. The model is dominated by routine to an extent that renders several alternative variables comparatively unimportant.

This finding supports our third research hypothesis and indicates that decisions regarding car ownership are sticky, and largely shaped by routines and habits, while other unobserved factors may also play an important role. Thus, policies that aim to motivate individuals to own fewer or no cars will also need to address and break routines and habits.

3.3 Stated reaction to policy measures

The final subsection presents our results on respondents' reactions to various policies – that is, their stated intention either to reduce their driving or abandon their cars altogether in response to specific policies. Due to various biases, this cannot be interpreted as empirical reaction. Responses are systematically upwardly biased due to respondents' potential to offer socially desirable responses and/or to overestimate their own ability to react in the stated manner and reliability may be low due to the hypothetical situation they respond to [61].

Instead, the results can be interpreted as rating the extent to which people consider policies to be effective. In general, approximately 40% of all respondents state that they would not curb their car use "at all" or "do not know," and about 50% state that they would not abandon their cars. Figure 5 shows that, in general, younger respondents report a stronger response to all policies investigated. Responsiveness to pricing policies is lower for high-income respondents. A reduction of commuter tax relief is stated to be less effective among those in lower income groups. Differences by population density are minor and do not follow a clear pattern.

As an example of a relatively more effective measure, financial reimbursement for going carless received positive ratings. About 60% of respondents in large cities and with high incomes and about 70% of respondents <30 years could imagine giving up their cars if they were paid a 5000€premium for doing so. A commuter tax relief was rated as less effective: here, only about 30–40% state that a reduction would make them abandon their cars.

The second set of questions covers other policies beyond pricing instruments. Items cover the stated probability of reducing car use or entirely abandoning the car. Here, we arrange responses in order of stated probability and plot a cumulative density function (Fig. 6). This allows us to see the percentage of respondents (y axis) who self-report as reacting with a minimum probability (x axis). In general, only a small fraction of the respondents (about 10%) state that they would reduce car use or abandon their car due to one of the surveyed policies with a probability >70%. Urbanisation, gender and income do not lead to strongly diverging results. Relative to older respondents, however, younger ones (< 30 years) state much higher probabilities: about 20% would reduce car use or abandon their car altogether.

Even if responses may be upward biased (see Sect. 2), results show that that impact of one single policy on car use and ownership is likely to be minimal. We can observe, however, that respondents see these policies as at least partially effective. We also observe within-differences: policies such as speed limitations, restricted private use of company cars, and prioritization of the cycling infrastructure are rated less effective than increasing car taxation or the legal right to work from home. Also, we find significant differences between age groups, probably related to routines. A relatively high certainty of reaction, though not absolute, indicates that some additional or combined push and pull measures [62, 63] may actually prompt respondent to act, showing that a consistent policy package is needed instead of isolated instruments if CO rates are to be changed. This finding supports our fourth research hypothesis, although the joint impact from a package of policies cannot be explicitly tested here.

4 Discussion

4.1 Socio-economic and socio-demographic context

Our results indicate that various factors are driving car ownership in Germany. Specifically, we find that household income, size, and structure are significant determinants of the number of cars owned. This is consistent with the findings of previous studies on CO in other countries [22]. CO also varies significantly across age groups. The trend observed by Kuhnimhof et al. [50], that younger generations often tend to forego car ownership, still holds true a decade later for the current generation of 18–29 year olds. This group is also much more policy-responsive than other groups (see Fig. 6). Interestingly, however, when households of 18–29 year olds do own vehicles, they tend to own more cars than do older generations. This could be one factor driving up the number of vehicle registrations.

The car ownership spread is especially large between urban and rural areas. There are various reasons for this. Urban areas offer better PT and cycling infrastructures, which we find to be a key determinant of car ownership, even if this finding is based on self-assessments and may be biased. Cities also offer shorter commutes to workplaces and basic services and thus an easier option to live without a car. This finding is also consistent with other studies [28–30, 49].

Independently of these factors, the population size of a person's place of residence plays a major role in CO decisions (see Fig. 3). This might reflect underlying factors like parking availability and congestion levels. We cannot however analyse rural areas with hometown size <5000 inhabitants and cannot differentiate between cities of >100,000 inhabitants due to data limitations. In these urbanisation segments additional interesting heterogeneity may be observed that needs further study.

Reliability was most often cited by car owners as an important factor for owning a car. Similarly, among non-car owners "do not need" was the most frequent response after cost considerations. A poor or decent public transport infrastructure significantly influences car ownership and non-ownership, respectively. On the other hand, PT pricing policies are not expected to effectively reduce CO, mainly because the required quality has not (yet) been ensured. Interestingly, reductions in commuter tax relief seem to have the least impact on CO decisions in low income groups. This might appear counter-intuitive, but could indicate a strong reliance on cars and a limited awareness of actual cost implications of the commuter tax relief.

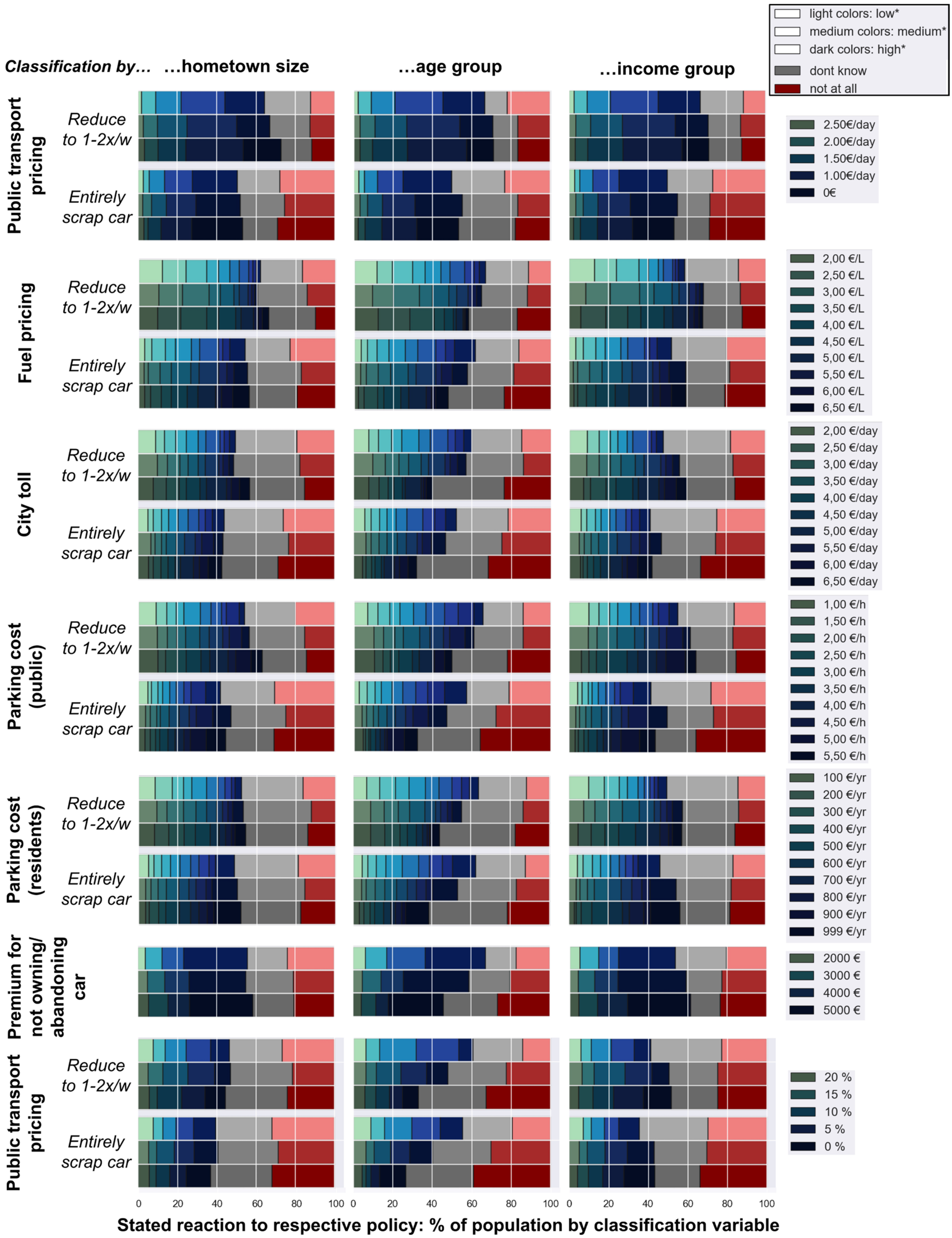

Fig. 5 Stated reaction to selected policy measures (by urbanisation, age and income). **Note*: hometown size classes: < 20,000, 20,000–100,000, 100,000+; age groups: 16–29, 30–59, 60+ yr; income groups: < 2600, 2600–3600, 3600+ €/hh

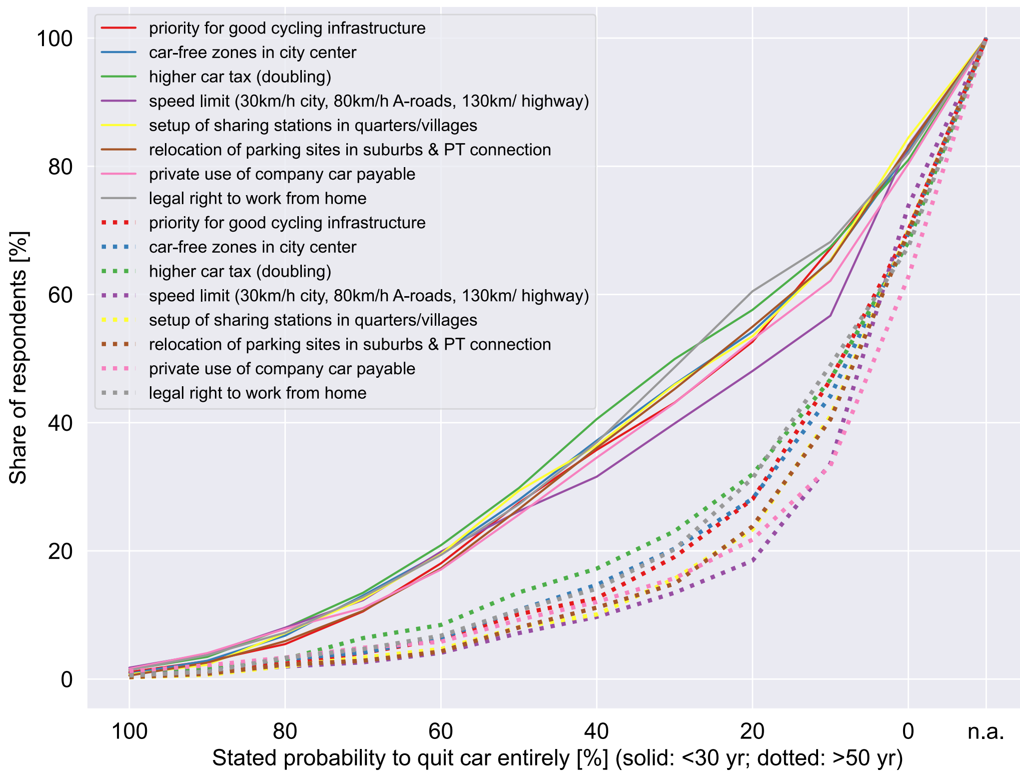

Fig. 6 Stated probability to quit car entirely due to selected policy measures (cumulative distribution by age group)

These findings support one key takeaway: The mobility culture in urban regions is characterised by a larger spectrum of mobility options, while rural regions are structurally more dependent on car use [33] due to inadequate PT infrastructure and frequency, poor cycling infrastructure and larger distances. An appropriate policy approach with pull measures is required counter the prevalent narrative that "in the countryside, you need a car". And to break high CO lock-in, also push measures are needed. Similarly, cities could activate their potential to reduce individual motorised transport by implementing strict policies and using residents' higher responsiveness to policies as a tool for reducing urban car ownership.

4.2 Individual and peer-group effects

Individual reasons for CO add new perspectives on the lock-in of CO status that we find it in the 'routine' model. Most commonly stated reasons by respondents for *not owning* a car are acquisition and running cost, while two thirds of the car *owners* state that it is cheap. This tendency supports the significance of income, which is a highly persistent factor. It also implies partial transport poverty, which is a broad phenomenon with multiple dimensions beyond the scope of this study [64]. However, when asked why they do not own a car, only about 16% of the respondents cite high costs and not "do not need". This hints at higher actual needs and thus social mobility restrictions, where people with mobility needs cannot afford to pay for it, as described in the literature [64]. Transport policies should address this social phenomenon, beyond the scope of environmental policies.

In our default model, we also find strong effects of the CO rate in the circle of family and friends on individual household CO status, supporting our third research hypothesis and in line with theoretical thinking on interpersonal behaviour [9]. When introducing routine into the model, significance of peer-group effect disappears, probably because of collinearity (peer groups remain relatively stable as do habits and thus do not explain additional variance).

4.3 Routine effects

Our 'routine' model support the third research hypothesis on the importance of routine effects, indicating that the habit of owning cars or living without a car is the strongest determinant of one's the current status. An interesting new finding is that households owning at least one car are more likely to then increase number of cars. Together with the high national ownership rate, this explains rising total car stock. Still, it is questionable whether our 'routine' model captures routine or habit in a psychological sense. It might also capture a large share of unobserved heterogeneity, i.e. factors not included in the survey and models. Some authors have argued that car ownership is the result of a complex decision chain over multiple trigger points over the life-course (e.g. birth of child, death of partner etc.) [42], that only panel-data analysis can analyse time-related issues [37–39]. Our cross-sectional dataset does not allow for panel analysis techniques. However, our results are consistent with findings from life-course event research, who similarly finds significant positive effects for age, income and number of adults, non-significant effects for number of underaged persons and employment [42]. This research however is limited to life-course events. Our approach additionally combines infrastructure, inter-personal norms, habit and socio-demographics.

These results add three insights to the field of knowledge. First, how long a person has maintained their current CO status is more relevant than their age group. This adds to the political challenge of tailoring policy instruments to specific generations while addressing all entrenched ownership habits across the board. Second, the perception of politically malleable CO determinants is significantly stronger when routine factors are dismissed (comparing the 'default' and 'routine' model), suggesting that policies should aim to break these routines. In other words, they should aim to intervene, not merely to moderate, and use windows of opportunity from life-course events that may allow substantial changes to routines [42]. Third, our findings suggest that choosing to go carless is more likely among those who have owned a car for shorter amount of time. Thus, focusing on young people and ensuring that they stay engaged with car alternatives would seem advisable.

Regarding the effect of certain pricing policies (see Fig. 5), our conclusions here are only tentative due to the hypothetical response bias and the gap between (stated) willingness to act and (actual) willingness to accept [61]. Nevertheless, some tendencies can be noted. Very high fuel prices and increased parking costs can be expected to effectively reduce the number of car trips and the number of cars owned. Especially effective would be a parking cost increase for residents in urban areas, as most respondents state their sensitivity to this policy. Public transport pricing has a notable effect only when it is entirely free; yet even when given free transport, most people affirm that they would keep their car. From the analysis of stated probabilities that individuals will alter their car ownership status in response to other policy instruments (Fig. 6), only a small share of the population surveyed affirm that they are highly likely to do so (about double the effect of car *use reduction*, see supplementary material Figure 41). However, we find interesting differences: younger people are at least twice as responsive than others to the idea of going carless, and the most effectively rated instruments are car taxation and the legal right to work from home.

All individual policies show similarly limited effects and no policy alone is likely to reduce CO dramatically. However, a large fraction of respondents reports a medium to high probability that it would go carless and can "imagine abandoning the car". An appropriate and stringent mix of push and pull measures is needed for a policy to be effective.

5 Conclusion: integrated policy packages for complex challenges

In this paper, we used cross-classification descriptive statistics, discrete choice models, and an analysis of stated policy responses to find a comprehensive set of determinants for car ownership in Germany. We discussed policies that could potentially reduce car ownership, and offered some concluding insights on push-pull policy intervention strategies.

Car ownership, we found, depends largely on the availability of public transport and of a cycling infrastructure, supporting our first initial research hypothesis. In rural Germany, the lack of a robust public transport infrastructure and the geographical spread of essential services drives a strong dependence on cars, lowering the expected impact of policy measures. Moreover, many households do not report the reason of not needing a car as central which may indicate their inability to afford a needed car. Strong pull measures to improve climate-friendly alternatives are required to address inadequate public transport infrastructures and to support social inclusion, especially in rural regions.

Findings from our default model support our second hypothesis: the higher the share of car ownership in respondent's peer groups, the more likely they are to own one or more cars.

But pull measures alone cannot significantly reduce car ownership. The shaping force of socio-demographic variables like age, income, and household size, alongside longstanding car ownership habits, render car ownership highly inelastic. Long-term ownership, in particular, acts as a lock-in factor that actually works to increase CO, with owners unlikely to change unless prompted to actively reflect on their needs. This supports our third hypothesis. The strong continuity in car ownership trends in Germany suggest that political and social framework conditions for car ownership have remained essentially unchanged over the course of recent decades. Against this background, important life-course events and major landscape events involving drastic transformation, like economic shifts, may provide opportunities for impactful interventions. Where habits perpetuate and even increase the number of cars per household, changing the car-centric infrastructures is key to break trends. These push and pull approaches therefore should be utilised when applying policy measures.

Given the limited effects of minor policy framework changes, stronger measures are needed to see significant reductions in car ownership, supporting our fourth hypothesis. The differences between rural and urban infrastructures and the powerful influence of habit mean that policies must be targeted and forceful. Successful cases and policy proposals exist in the literature [29, 63, 65]. Specifying the most effective policy mix [66] and understanding their challenges and potential benefits remain subjects for future research.

As is usual in complex systems like transport, single policy measures likely will not be effective. Rather, integrated policy mixes comprised of both pull and push measures are needed to reduce car ownership in Germany. Proposed policy examples include substantial shifts in funds from road to public transport, enabling higher frequency, capacity and quality of public transport in both rural and urban regions; and consecutively strong push measures like pricing of car tenancy, fuel, roads, parking, the rededication of road and parking space to other uses like walking, cycling or green areas and car access restrictions to city centers [65, 67].

Future research should focus on understanding which factors can influence changes in car ownership, rather than only explaining the status quo. Specific next steps could involve carrying out discrete choice experiments on changing patterns of car ownership, applying mixed logit models to study heterogeneities in the base population and identify niche groups, and integrating CO models into full-scale transport models in order to study the potential effects of CO change on the overall mobility system.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12544-024-00699-1.

Additional file 1.

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Author contributions
Johannes Thema: Conceptualisation, Methodology, Software, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing - Original Draft, Visualisation. Julian Reul: Methodology, Software, Formal Analysis, Data Curation, Writing - Review & Editing, Visualisation. Marlin Arnz: Conceptualisation, Methodology, Validation, Writing - Original Draft. Frauke Wiese: Conceptualisation, Validation, Writing - Review & Editing, Supervision.

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Availability of data and materials
The dataset supporting the conclusions of this article is available in the Zenodo repository, DOI:10.5281/zenodo.7353641, https://zenodo.org/records/7353641. The jupyter notebook with the python script for all descriptive analyses supporting the conclusions of this article is included within the article references, the resulting graph outputs as supplementary material. The MO DE.behave framework is available from the Github repository, https://github.com/FZJ-IEK3-VSA/mode_behave under an open MIT licence.

Declarations

Competing interests
The authors report that there are no Conflict of interest to declare.

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