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The effects of spatial characteristics on car ownership and its impacts on agent-based travel demand models

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Abstract

The objective of this study is to investigate the role of spatial characteristics on car ownership and availability respectively in agent-based travel demand models and its affection on the model's results. Based on Open Data we generate an automated workflow to evaluate spatial characteristics such as land use, points of interest, private vehicle network, and public transport quality. We estimate two multinomial logit models for car ownership: one considering socio-demographic characteristics only, and one considering both, socio-demographic and spatial characteristics. The models' results are spatially evaluated and compared with statistical data. Moreover, we analyze the sensitivity of public transport quality measures on car ownership. The application of both car ownership models in the agent-based travel demand model mobiTopp to the city of Hamburg, Germany shows that integrating spatial characteristics significantly improves the model's goodness of fit as well as its overall prediction power. Moreover, the application demonstrates that a detailed consideration of spatial characteristics in car ownership models contributes to a more realistic spatial distribution of cars. Furthermore, the study shows that i.e., public transport quality measures in car ownership models are relevant to reflect secondary mode choice effects (i.e., different mode choice sets due to change in car stock) in travel demand models.

Keywords: car ownership; car availability; spatial characteristics; agent-based; travel demand; open data

1. Introduction

Travel demand models (TDM) are common tools in transport planning to evaluate the success of various measures. Whereas aggregated TDMs can only simulate mobility behavior for certain person groups, agent-based TDMs simulate individual mobility behavior. Hence, they allow for more interrelations and for the simulation of more

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complex behavior. The individual mode choice decision is, among other aspects like preferences or trip characteristics (primary effects), strongly influenced by the ownership or non-ownership respectively availability of a car. Only if a car is available for an agent, it can be considered as an alternative in mode choice. Consequently, a change in car stock always leads to different mode choice sets (secondary effects).

Models for predicting car ownership exist since the 1930s [1] and have been continuously developed since then [2–4]. In the early years the observation level of these models was predominantly aggregated. With the development of suitable model algorithms (e.g., discrete choice models) as well as increasing data availability and computational power, disaggregated models at the household or person level have become also state of the art. In de Jong et al. [5] nine types of models are distinguished. Since this paper focuses on disaggregated models for use in transport-related agent-based models (ABM), we refer to this article for a detailed overview of all model types prior to 2004.

Nowadays the state of the art are appropriately disaggregated car ownership models in the form of discrete choice methods. Although the details (like model types and structures as well as the independent variables) of the car ownership models in transport-related ABMs are often not published, to the authors knowledge, mostly simple multinomial logit (MNL) or binary logit (BL) approaches with socio-demographic variables are used. Horni et al. [6] provide a good overview of methods used for the transport-related ABM MATSim (e.g., Chapter 57, page 379 or 386). However, many academic publications highlight the relationships between car ownership and spatial factors, such as built environment or the range and quality of alternative modes, whereas common disaggregated approaches mostly rely on engineered spatial features, such as density [7, 8] and accessibility [9, 10] measures. Engineered features have the disadvantage of not being able to clearly identify the direct influence of spatial variables that define the engineered feature itself. Even so, there are only a few car ownership models as part of transport-related ABM considering spatial variables. Moeckel and Yang [9] developed a car ownership model for the agent-based land-use model SILO [11]. Jonnalagadda et al. [12] applied rough accessibility and area type measures in their travel demand model for San Francisco in the early 21st century. Van Eggermond et al. [13] used a BL approach which considered information about points of interest (POI), accessibility to public transport (PT) stations and accessibility of workplaces with PT of household members to assess car ownership for a transport-related ABM of Singapore. Hillel et al. [14] used a sequential approach with BL and MNL models to model driver's license, car, and public transit pass ownership for the transport-related ABM SIMBA MOBi based on socio-demographic variables and spatial information, such as engineered accessibility measures, and population densities. The quality of public transport, however, is not only determined by accessibility measures like the nearest stops or the travel time (especially when calculated just with single PT connections) to certain destinations. Frequency and consistency of the PT service during the day are also important factors [15]. To the authors' knowledge, there are no car ownership models implemented in transport-related ABMs that explicitly consider the latter influences up to date and hence, can quantify the isolated effects of e.g. accessibility in terms of the nearest stops or frequency of PT. In addition, novel and open-access datasets are available nowadays for a more detailed and more comprehensive evaluation of spatial characteristics that have not yet been fully utilized in existing car ownership models.

Consequently, the spatial distribution of car ownership cannot be captured by the TDM to that extent and transparency that would be possible with today's detailed data on the one hand, which implies a higher spatial inaccuracy of the TDM itself. On the other hand, secondary mode choice effects cannot be simulated accurately. This might not be relevant for the evaluation of every measure, especially not for such measures with short-term effects (e.g., road closure due to construction work). But for measures with long-term effects, such as desired modal shifts to environmentally friendly alternatives, this could restrict TDMs to be sensitive for primary mode choice effects only. Hence, if measures are investigated with the help of a TDM, then sensitivities of those measures on car ownership need to be considered as well to correctly determine the resulting effects.

Therefore, the aim of our work is to develop a car ownership model for the agent-based TDM mobiTopp, which first, improves spatial distribution of car ownership and hence, spatial accuracy for the TDM itself and second, enables the model to simulate also secondary mode choice effects. To make the approach transferable, only Open Data sources that are available at least on national level will be used. In addition, an automated workflow is created that allows the application in other regions with low effort. This paper is organized as follows. First, we give an overview of the microscopic travel demand model mobiTopp we applied in our approach. Second, the data base used for the creation of the spatial characteristics as well as the description of the estimated car ownership models is presented. Third, we show our results and explain how we evaluated them. Finally, we give a conclusion.

2. Microscopic travel demand model mobiTopp

In this study we use mobiTopp as modelling environment. The open source software mobiTopp is an agent-based travel demand simulation, in which every person of a designated planning area is modelled as an individual agent [16]. For each agent, a distinct activity program is generated and executed during the simulation period [17]. Based on discrete choice models, an agent chooses the destination where an activity is performed as well as a mode to travel to the chosen destination. The simulation period is one week with a temporal resolution of one minute. Spatially, mobiTopp is based on travel analysis zones (TAZ) – polygons that divide the planning area in small units.

mobiTopp consists of two modules, the long-term and the short-term module. In the long-term module, a synthetic population is generated. Based on aggregated statistical data and data of a household travel survey, households and persons are generated for each zone setting the corresponding zone as home zone for each household member. Also, the workplace or the location of educational institutions of the agents are determined as fixed locations. Further characteristics of the synthetic population are modelled separately based on data of household surveys. This includes the number of cars owned by each household which is used to consider car availability during the subsequent simulation. The car ownership model is described in detail in a latter section. Additionally, logit models are used to determine additional mobility tools, e.g., a public transit pass. All characteristics determined in the long-term module remain fixed over the simulation period.

In the short-term module the agents' activity-based mobility behavior is simulated simultaneously. Agents execute their given activity program chronologically. For activities with flexible destinations, destination choice is conducted based on activity-specific attractivity measures for each TAZ. To reach the destination, an agent also chooses a mode from a subset of available modes, which depends on car availability within the household and the mode chosen for the first trip of a tour. The decision process is repeated for each activity in an agent's activity program. A detailed model description is given in Mallig et al. [18], Briem et al. [19] or Mallig and Vortisch [16].

In this paper we refer to a recent application of the model in the city of Hamburg, Germany and surrounding areas. The model comprises more than 4 million persons and more than 2,500 TAZs. The present study only focuses on the city area representing more than 1 million households in approx. 1,500 TAZs.

3. Data

The data for our models is derived from various data sources. As behavioral part of the data, we used a household travel survey. The spatial context was set up using Open Data sources with geographical and PT-related information.

3.1. Household travel survey (HTS)

As behavioral data, we used the German national HTS "Mobility in Germany 2017" (MiD) with detailed spatial references (B3 data set) [20]. Among others, the survey data contains information on household, person, and trip level. Since the car ownership model of mobiTopp is applied to the agents' households, we only used household information of the participants. To restrict on regional behavior of the planning area, only households located within this area were selected. The survey offers a comprehensive sample for Hamburg. Due to privacy issues, car ownership is captured with the three classes *no car, one car* and *two or more cars*. Furthermore, we had to delete households with relevant missing values from the dataset, e.g., missing information about the number of cars owned. Moreover, we omitted all households in which no household member has a driving license as those households deterministically can be assigned no car. Hence, for those households the car ownership model will not be applied. This resulted in 13,906 households left that could be used for model estimation. Finally, based on the households' geographical location, we analyzed and added the spatial variables described in the next subsection to our dataset.

3.2. Spatial data

Geographic information as well as information on PT accessibility and quality were gained from Open Data sources. We aimed to use open-access and highly detailed data with wide spatial coverage and global use, as applicability to other regions and countries should be supported. We used OpenStreetMap [21] as source for land-use information, points of interest (POI) and private vehicle network indicators, as well as Corine Landcover data [22] as second source for land-use information. For information about PT accessibility and quality, we used German-wide data in GTFS format [23]. Since we did not know, which information was significant for car ownership, we first created various feature variables regarding land-use, POIs, private vehicle network quality and PT accessibility and quality (see Table 1). We decided to apply an exploratory rather than a literature-based approach for the creation of feature variables. Hence, we defined the maximum number of possible feature variables we could create from GTFS and OpenStreetMap as well as Corine Landcover data considering only 'raw' feature variables instead of engineered features. Hereby, we aimed to let the model decide, which single variable has a significant impact and which not. For a detailed description of land-use, points of interest (POI) and private vehicle network feature variables we refer to the OpenStreetMap Wiki [24]. Each feature variable was computed for each area (estimation: grid cells, model: TAZ). For this we created a workflow that automatically collects and analyzes the corresponding data. The code has already been stored on GitHub and will be published soon. We further used a Random Forest model with car ownership as dependent variable, and all created featured variables as independent variables to determine the variable with the most influence on car ownership using variable important measures (VIM). Although VIM cannot provide quantitative measures of variable importance for predicting the dependent variable output, it allows for a qualitative but ranked assessment. We finally chose all variables with a VIM value of 1/10 of the maximum VIM value to include in the car ownership model and test for significance.

Table 1: Created feature variables from Open Data

Spatial information	Source	Feature variables
Land-use	OpenStreetMap, Corine Landcover	Shares of land-use categories (recreational, agricultural, transportation, pastures, commercial, residential, nature) for each area
POIs	OpenStreetMap	Number of POIs for each category (shopping daily, shopping other, leisure food culture, leisure sport parc, leisure other, education, personal business, health, accommodation, tourism) in each area
Private vehicle network	OpenStreetMap	Road densities in km/km² for each street type (residential, primary streets, highways) for each area
PT accessibility / quality	GTFS (gtfs.de)	Number of PT stops for each PT system (bus, tram, metro, commuter train) in each area
		Mean frequency over all stops for each PT system (bus, tram, metro, commuter train) in each area
		Standard deviation of frequency over all stops for each PT system (bus, tram, metro, commuter train) in each area
		Number of all PT services for all stops for each PT system (bus, tram, metro, commuter train) in each area
		Number of all PT lines for all stops for each PT system (bus, tram, metro, commuter train) in each area
		Numbers of hours with no/1-2/3-5/6-12/12+ PT services per hour over all stops for each PT system (bus, tram, metro, commuter train) in each area

Figure 1 presents descriptive characteristics of a selection of feature variables included in our model. The analysis uses the spatial data computed for the TAZs in mobiTopp. Missing values for zones, e.g., where no PT is available, are not included. The values of the selected PT quality measures vary greatly. While the median of the mean number of bus services is about 95 for all stops per zone, the median of the mean number of bus lines of all zones in mobiTopp is only 2. The number of POIs of the selected variables are roughly equally distributed, while greater outliers of POIs for food and culture as well as personal business are observable. Furthermore, one can see differences in the values of selected road density variables. This is reasonable, since residential streets are widely distributed over a city area, whereas motorways e.g., are only built in selected corridors and therefore require less space in total. The selected land use variables show that most of the zones have a low share of land use for transportation in comparison to other land use categories.

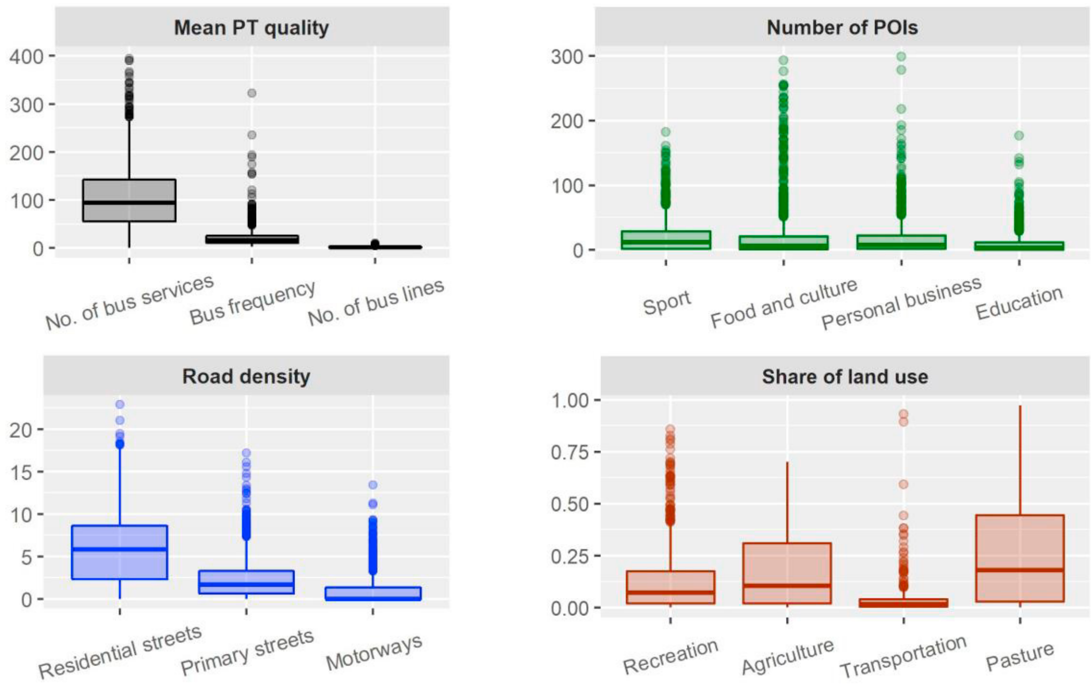

Figure 1: Descriptive results of spatial variables incorporated in the later model

4. Model estimation

For the model estimation we used the R-package *apollo* [25]. To identify the best model fitting to our data, we estimated different types of discrete choice models: multinomial logit models (MNL), nested logit models (NL) and ordered logit models (OL). For all model types the choice variable was identical (*no car*, *one car* and *two or more cars* per household). We started with a base MNL, NL, and OL model, respectively, comprising only the alternative specific constant. Successively, we tested further variables in our models beginning with the households' socio-demographic characteristics and continuing with the spatial variables. The decision whether a variable was included in the final model specification was based on its statistically significant influence requiring a significance level of at least 10%. We did not further consider the NL models as the λ-parameters were close to 1 in all model specifications. Hence, the models were similar to a regular MNL model. As a result, we estimated two MNL and two OL models, one only with household characteristics and one with both, household and spatial characteristics.

Table 2 shows the results of the estimated models. First, both model types, MNL and OL, have a better global goodness of fit when spatial variables are included. Besides improving the log-likelihood and thus the adjusted R-square or McFadden Pseudo R-square, respectively, also the values of Akaike (AIC) and Bayesian Information Criterion (BIC) could be reduced, although additional parameters have been added to the model. Second, both MNL models show strictly better global goodness of fit measures than the corresponding OL models.

Table 2: MNL and OL model results; with and without spatial variables (SV)

	MNL		OL	
	Without SV	**With SV**	**Without SV**	**With SV**
Log-Likelihood (final)	-10,447.7	-9,660.6	-10,677.4	-9,910.6
AIC	20,937.4	19,419.2	21,380.8	19,877.3
BIC	21,095.8	19,788.7	21,478.8	20,088.4
Adj. R-square (0)	0.315	0.364		
Adj. R-square (constants)	0.221	0.280		
McFadden Pseudo R-square (0)			0.093	0.104
N				13,906

Consequently, we decided to model car ownership using the MNL. The results of the parameter estimation of both models are given in Table 3. Household attributes were dummy coded. Spatial variables were metrically scaled. As the value range differs between the spatial variables, the absolute values of the parameters are not directly comparable.

Regarding the household attributes, the MNL models with and without spatial characteristics show similar effects. Households with an increasing economic status (normalized household income by number of household members) are more inclined to own cars. Additionally, the household type also contributes to the explanation of car ownership. Being a family household with children has a stronger positive effect on owning a car than other household types. This is probably caused by a higher complexity in parents' trip chains that cannot be satisfied sufficiently by other modes. It is not surprising that with an increasing number of household members holding a driving license it is more likely to own cars. Moreover, it is noticeable that after introducing spatial variables to the MNL, the estimates for household size and number of driver's license remained almost constant, while the estimates for economic status and household type changed. Therefore, we assume that the latter correlate with spatial variables, whereas household size and number of driver's license seem to be spatially independent variables.

Table 3: Estimated parameters of MNL models

β – parameters of MNL-models	***Without spatial variables***		***With spatial variables***	
	$U_{a,1\ car}$	$U_{a,\geq 2\ cars}$	$U_{b,1\ car}$	$U_{b,\geq 2\ cars}$
Alternative specific constant	-1.194 ***	-5.266 ***	-0.327 *	-3.988 ***
Household attributes (blanks as base)				
2-person household	0.320 ***	0.522 ***	0.396 ***	0.554 ***
Very low economic status				
Low economic status	0.255 **		0.430 ***	0.582 ***
Medium economic status	0.927 ***	0.885 ***	1.112 ***	1.506 ***
High economic status	1.030 ***	1.845 ***	1.342 ***	2.686 ***
Very high economic status	0.947 ***	2.093 ***	1.391 ***	3.213 ***
Household with people ≤ 35 years				
Family household with children	1.605 ***	2.671 ***	1.347 ***	1.974 ***
Family household without children	1.089 ***	2.099 ***	0.823 ***	1.385 ***
Household with people ≥ 65 years	1.527 ***	1.892 ***	0.988 ***	0.817 ***
1 driving license				
2 driving licenses	1.057 ***	3.488 ***	0.997 ***	3.434 ***
More than 3 driving licenses	1.411 ***	5.405 ***	1.342 ***	5.213 ***
Spatial characteristics of home zone				
Mean no. of bus services			-0.001 ***	-0.003 ***
Mean bus frequency			0.002 ***	0.002 ***
Mean no. of bus lines			0.107 ***	0.155 ***
Road density of residential streets			-0.037 ***	-0.060 ***
Road density of primary streets			-0.100 ***	-0.160 ***
Road density of motorways			-0.874 ***	-0.143 ***
POI for sport activities			-0.002 *	-0.011 ***
POI for food and culture			-0.005 ***	-0.006 ***
POI for personal business				-0.004 ***
POI for educational activities			-0.007 ***	-0.012 ***
Recreational land use			-1.215 ***	-1.689 ***
Agricultural land use			2.146 ***	3.188 ***
Transportation land use			-1.814 **	-8.486 ***
Pastures land use			1.481 ***	1.845 ***

Parameters marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

Besides the better model fit, the parameters of the MNL with spatial variables show interesting facts regarding the decision taking to own a car. According to *PT quality measures* at a household's residential area, only variables describing the quality of buses were significant. With only 4 metro lines, Hamburg's metro system has a comparatively low density. Hence, buses play an important role in Hamburg's PT system. The model shows that people living in areas with a better bus service or a denser bus frequency are less likely to own cars. Nevertheless, increasing the number of bus lines has a positive effect on owning a car. Hence, just increasing the number of bus lines seems not to convince people to abolish cars: a consistent service with a dense frequency is required. Further, a higher *road density* at a household's residential area has a negative effect on owning cars. A high road density can be associated with more urban areas, where owning a car might be less attractive than in rural areas. This also applies for the *number of POIs* explaining the negative sign of the corresponding parameters. In line with these findings are also the parameters for *land use* characteristics at peoples' home. People living in rural areas (corresponding to an agricultural or pastures land use) are more likely to own cars, as other mode alternatives may not be available. In contrast, people living in areas with high shares of transportation land use (share of land use utilized for transportation purposes) have multiple alternative modes and might therefore be less likely to own a car.

5. Results

The previously described models have been integrated in mobiTopp. Hence, the models have been applied to the synthetic population, representing the car ownership in the city of Hamburg. To obtain comparability between the model results, we did not calibrate the parameter estimates. According to our research objectives, the results focus on two aspects. First, we show major differences in the spatial distribution of car ownership between the MNL with and without spatial variables and compare the model results with statistical data. Second, we evaluate the importance of integrating spatial variables in car ownership models for secondary mode choice effects in TDMs by evaluating model sensitivities based on simple PT measures.

5.1. Spatial distribution of car ownership

To understand if the estimated models reflect the actual distribution of car ownership in Hamburg, a comparison with statistical data of the corresponding planning area is necessary. We used data on private car ownership in Hamburg as of January 2020 provided by the local registration authority [26]. The dataset aggregates the information about the number of registered cars at the level of 104 districts within Hamburg. For comparison, the zone structure in mobiTopp was matched with the city districts and the number of modeled cars was cumulated accordingly. Furthermore, as we did not calibrate the parameters of both MNL models, the overall number of cars in mobiTopp was scaled to the number of cars given in the data of the registration authority keeping the relative distribution of cars fixed. Finally, the differences between modeled and actual car ownership were calculated for each district and related to the number of residents living in each district.

The median absolute difference over all districts for the MNL without spatial variables is 73 cars/1,000 residents. In contrast, the median absolute difference for the MNL with spatial variables is 58 cars/1,000 residents. Furthermore, also the 1st and 3rd quartile is clearly lower, indicating that integrating spatial variables in a car ownership model can better describe car ownership. Those descriptive findings can also be supported statistically. As the number of observations is greater than 30, normal distribution was assumed. Hence, a paired t-test was conducted to investigate if the mean absolute difference for the MNL with spatial variables is significantly lower than the corresponding mean of the model without spatial variables. With a test statistic of $t = -4.917$ and 102 degrees of freedom, the p-value of $<.000$ is supporting our hypotheses.

Besides the overall differences we also analyzed the spatial accuracy of both MNL models versus statistical data provided by Hamburg's registration authority. The results are shown in Figure 2 (a). The districts are shaded by the actual number of cars per 1,000 residents. The differences of both MNL models versus the statistical data are indicated by differently colored and directed bars per district. It is noticeable that in districts with an already high car ownership both MNL models underestimate the number of cars, whereas in districts with a comparatively low car ownership the opposite effect can be observed. Nevertheless, the MNL with spatial variables generally reflects the statistical data better as the differences are lower. Exceptions occur mainly in districts with a lower car density and where less people live. As the car density is a relative measure according to the number of residents, the absolute difference is rather small. Furthermore, in districts with a medium number of cars per 1,000 residents, only minor differences between both model predictions are observable. In these districts, however, both models are already quite close to the statistical data. When not considering spatial variables in car ownership models, the prediction seems to be close to a mean value as spatial differences are not covered. This explains the quite accurate prediction of the MNL without spatial variables in districts with a medium number of cars per 1,000 residents.

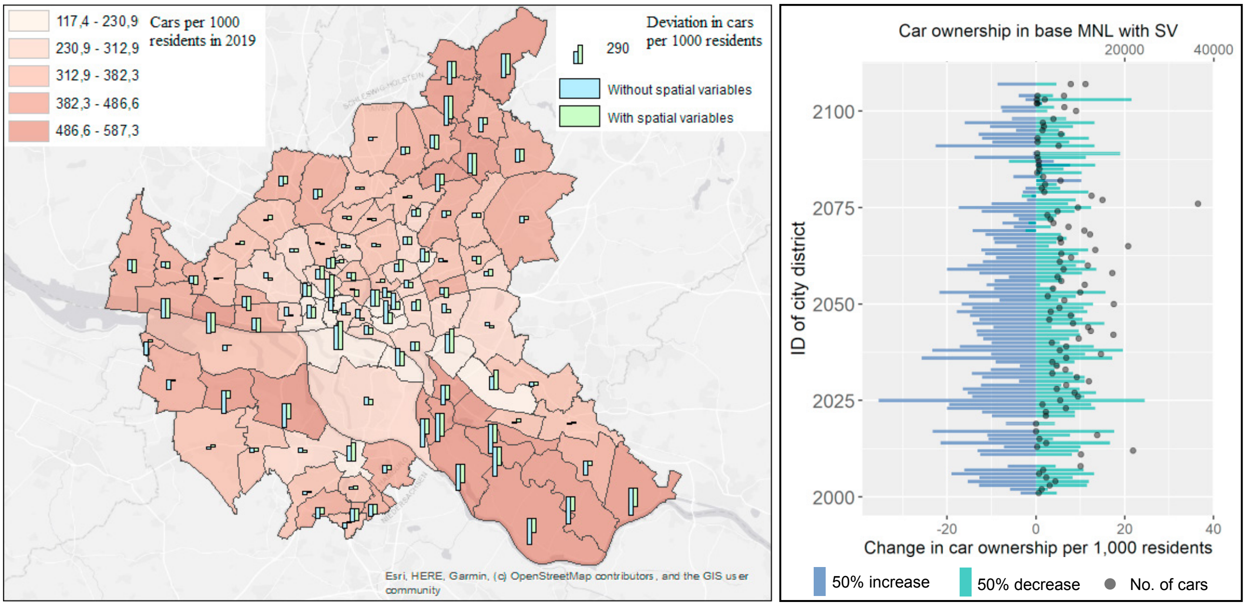

Figure 2: (a) spatial distribution of differences between MNL model results versus statistical data; (b) change in car ownership by adjusting bus quality variables in MNL with spatial variables (SV)

5.2. Model sensitivities of PT measures

We further investigated the sensitivity of spatial measures on car ownership and analyzed how the model prediction of car ownership changes when spatial measures vary. In this study we focus on the effects of changes in PT quality measures since other aspects such as land use, number of POIs, and road density differ only slightly within a typical planning period covered by a TDM. In addition, the effects of changes in PT quality on one's mobility behavior are of particular interest to transportation planners. We set up two scenarios, one with an 50% increase of PT quality, and one with a 50% decrease, respectively. According to the variables integrated in the presented MNL model, we consequently adjusted mean bus service, mean bus frequency, and mean bus lines. Therefore, the simulations of both scenarios are restricted to changes in bus quality.

Figure 2 (b) compares the results of both scenarios. The bars show the change in the number of cars per 1,000 residents for each district in comparison to the base MNL model, where PT quality variables were not adjusted. It becomes clear that an increase in bus quality reduces the car ownership on average. In contrast, decreasing the bus quality increases the number of cars per 1,000 residents on average. This is in line with our expectations and supports the hypothesis that considering PT quality in car ownership models can reflect secondary mode choice effects. Few exceptions occur in districts in outer city areas (district ID > 2070). It is noticeable that in these districts the number of cars is in general very low. In both scenarios, the change in the number of cars per 1,000 residents varies among the districts and is not equal to a mean value over all districts nor correlates with the number of cars. This, again, shows that our model is responsive to spatial differences. Moreover, the differences are symmetrically distributed among the districts, meaning that a lower change in the number of cars in one scenario also corresponds with a lower change in the other scenario. This is reasonable as in both scenarios the adjustment of bus quality variables were of the same level (50%) and started from the same basis. Nevertheless, the overall number of cars in Hamburg is predicted to decline by 2,7% when bus quality increases by 50%, whereas it is predicted to rise by 2,0% when bus quality decreases by 50%, respectively. The comparatively low model sensitivities are in line with existing literature. For example, Mulalic and Rouwendal [27] found out that a doubling of metro stations in the Greater Copenhagen Area, Denmark, reduces car ownership only by 2-3%. Although bus quality was adjusted at the same level, the effect of the decrease in the number of cars is greater than that of the increase. One can state that the degree of car ownership in industrialized countries is already in a saturated state. Hence, people are more likely to abolish cars (e.g., the 2nd car of the household) than to acquire additional ones.

6. Conclusion

In the present study, we showed that integrating spatial variables (i.e., PT quality, POI density, road density, and land use) in car ownership models can significantly improve the model's goodness of fit and its overall prediction power. Policy makers can use the influences of considered spatial variables to derive appropriate measures. Furthermore, we demonstrated that considering spatial variables contributes to a better spatial distribution of car ownership and hence, leads to a reduction in spatial inaccuracies. We also showed that considering PT quality measures (i.e., frequency and consistency) in car ownership models are relevant to reflect secondary mode choice effects in travel demand models. When PT measures are not only addressed in the short-term mode choice, but also in the long-term decision of car ownership, we assume to simulate corresponding effects more realistically.

Nevertheless, analyzing long-term effects in transportation planning requires a comprehensive data base to compare modeled results with reality. The GTFS data used to determine the PT quality variables are only available in the required granularity as of 2017. Data from previous years would be necessary to compare the modeled effects of PT measures on car ownership with real data. Although our model showed overall reasonable results, we also identified few outliers. Hence, we also need to improve our method in order to increase the prediction power in those districts as well. Therefore, we will test further spatial features to be considered in our car ownership model. Policy makers could then able to derive suitable measures based on not yet considered spatial variables. Applying non-linear models will be considered in a future work. Furthermore, it might also be interesting to analyze the interaction between secondary and primary mode choice effects in more detail. Based on changes in the modal split, we need to analyze to what extent both effects contribute to the final mode choice in mobiTopp. In addition, the current work was done for the city of Hamburg. We further plan to investigate, whether the selected spatial variables provide potential to easily transfer the existing car ownership model to other regions without the need for estimating a new model.

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