Where are Cars Parked at Home? Determinants of Residential Parking Location Choice

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Short summary

This paper uses data from the 2023 German national travel survey to investigate residential parking location choice. A two-step modeling framework has been developed using multinomial logit models. The results show that spatial characteristics and intra-household consistency are the most influential determinants, whereas vehicle and household attributes play a minor role. Overall, private off-street parking dominates, though significant variation exists across urban contexts and socioeconomic groups. The proposed methodology can be transferred to other national travel surveys and integrated into agent-based travel demand models to improve mode choice modeling, thus supporting the design of more effective transport policies.

Keywords: agent-based modeling, discrete choice modeling, national travel survey, off-street parking, on-street parking, residential parking location

1 Introduction

Cars spend over 95% of their time parked, most of it at home (Bates & Leibling, 2012; Button, 2006). Yet, even in high-density urban neighborhoods with substantial on-street parking pressure, private parking infrastructure often remains underutilized (Scheiner et al., 2020; Taylor, 2020).
At the same time, reliably estimating the overall supply of private parking still poses a challenge. Therefore, effective policy design requires a better understanding of the determinants of residential parking location choice, even if the exact number of private parking spaces is unknown.
While many studies focus on the impact of parking conditions at the destination (Ben Hassine et al., 2022; Chaniotakis & Pel, 2015; Guo, 2013b), residential parking supply also influences both car ownership and travel behavior (Christiansen et al., 2017; Guo, 2013a,b). Incorporating residential parking location into agent-based travel demand models therefore enables a more realistic representation of travel behavior.
Guo (2013a) shows for New York City that residential parking supply is a key determinant of household car ownership and can even outweigh the influence of sociodemographic characteristics and income. Similarly, Christiansen et al. (2017) find for Norway that access to private or reserved parking triples the probability of car ownership. With respect to travel behavior, according to Guo (2013b), the availability of residential off-street parking increases the likelihood of car use by ensuring reliable parking at the residence. Furthermore, Christiansen et al. (2017) identify a negative correlation between walking distance to the residential parking location and car use.
National travel surveys (NTS), which are conducted in many countries, provide a valuable data source for analyzing residential parking behavior. According to Porschen & Kuhnimhof (2025), more than 60% of analyzed NTS include information on residential parking, predominantly in Europe. While survey designs differ with respect to their unit of analysis (vehicle, household, or individual) and level of detail, they offer important insights into residential parking behavior.
Thus, this paper models vehicle-level residential parking behavior using data from the German NTS Mobility in Germany 2023 (infas et al., 2025). It identifies key determinants of residential parking location choice, including intra-household relationships, and develops a transferable methodology applicable to countries with comparable survey data. The resulting model can be integrated into agent-based travel demand models to support evidence-based policy design.
The remainder of this paper is structured as follows. Section 2 introduces the German NTS and provides descriptive statistics on residential parking choice. Section 3 outlines the model structure, followed by results in Section 4 and a subsequent discussion in Section 5.

2 Data

In this paper, the large-scale national household travel survey Mobility in Germany 2023 serves as data source, providing comprehensive cross-sectional data on mobility patterns in Germany. The dataset contains information on individuals, households, and trips on a reference day, as well as detailed information on household vehicles for a subset of participants.
The data is available at varying levels of anonymization and spatial detail. We employ the B1 dataset, which provides the most detailed information on socioeconomic characteristics and includes a car module. This module is required, as it is the only component containing information on residential parking locations at vehicle level. In terms of spatial resolution, the data is limited to pre-computed indicators, such as regional types distinguishing between different urban and rural areas, public transit accessibility, or characteristics of the built environment. Thus, when using the car module, no additional spatial characteristics can be merged from external data sources.
We combine the NTS car module with person- and household-level attributes, resulting in a comprehensive database of approximately 85,000 cars across 54,000 households for model estimation. To provide a better understanding of the underlying data, the following section presents descriptive insights into how vehicles are parked at home.
In total, four types of residential parking choice are distinguished in the NTS: on-street parking, on-street parking with a residential permit, public off-street parking, and private off-street parking. Figure 1 illustrates the distribution of parking spaces at the place of residence for the full sample, differentiated by regional type based on the seven-level Regional Statistical Spatial Typology (German Federal Ministry of Transport, 2020) and by the number of cars per household. Overall, 72% of cars are parked in a garage or on private property, whereas only 17% are parked on-street without permit. However, across different region types, the share of private residential off-street parking ranges from 43% to 92%, while on-street parking accounts for 7% to 28%. Thus, only a relatively small proportion of cars is directly affected by limited parking availability or parking policy measures - particularly in light of underutilized private parking infrastructure. However, lower-income households are disproportionately affected by on-street parking regulations at the residency, since higher-income households park their cars privately off-street more often.
Further, Figure 1 indicates that households with more than one vehicle (approximately 26,000 households) are more likely to use private off-street parking for at least one of their cars. When analyzing the consistency of parking behavior across vehicles within these households, more than 75% of the households use the same parking location at home for both vehicles. In cases where parking differs between cars, the most common combination (75%) consists of one car parked in private off-street parking and the other parked on-street without permit.

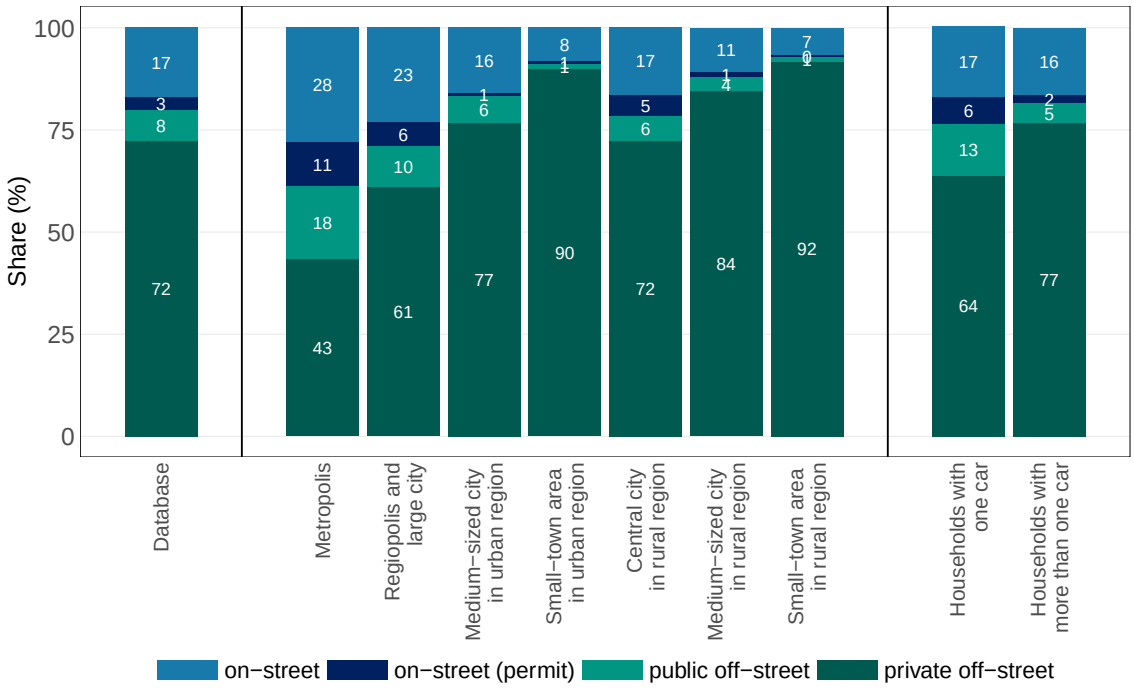


Figure 1: Residential parking location by region type and number of cars per household.

3 Methodology

We model the typical residential parking infrastructure as dependent variable, distinguishing between on-street parking, on-street parking with a residential permit, public off-street parking, and private off-street parking. Vehicle, household, and spatial variables from the German NTS serve as predictors in multinomial and nested logit models.
As a first modeling step, the entire database (84,549 vehicles) described in Section 2 is used to model the typical residential parking location for any vehicle within a household. In a second modeling step, we incorporate dependencies across multiple household vehicles. Therefore, the typical parking location of one household car is included as explanatory variable in the estimation. Given that household vehicles may be ranked according to various criteria, like usage frequency, vehicle size, status, or parking location, and that a consistent ranking within a household is not always feasible, a stochastic approach is employed to model intra-household behavior.
For this, the dataset is restricted to households owning two or more cars. Subsequently, one vehicle per household is randomly selected and its observed parking location is assigned to the other vehicles in the household as an additional variable. The selected vehicle is then removed from the sample. The process of data preparation and model estimation is illustrated in Figure 2.

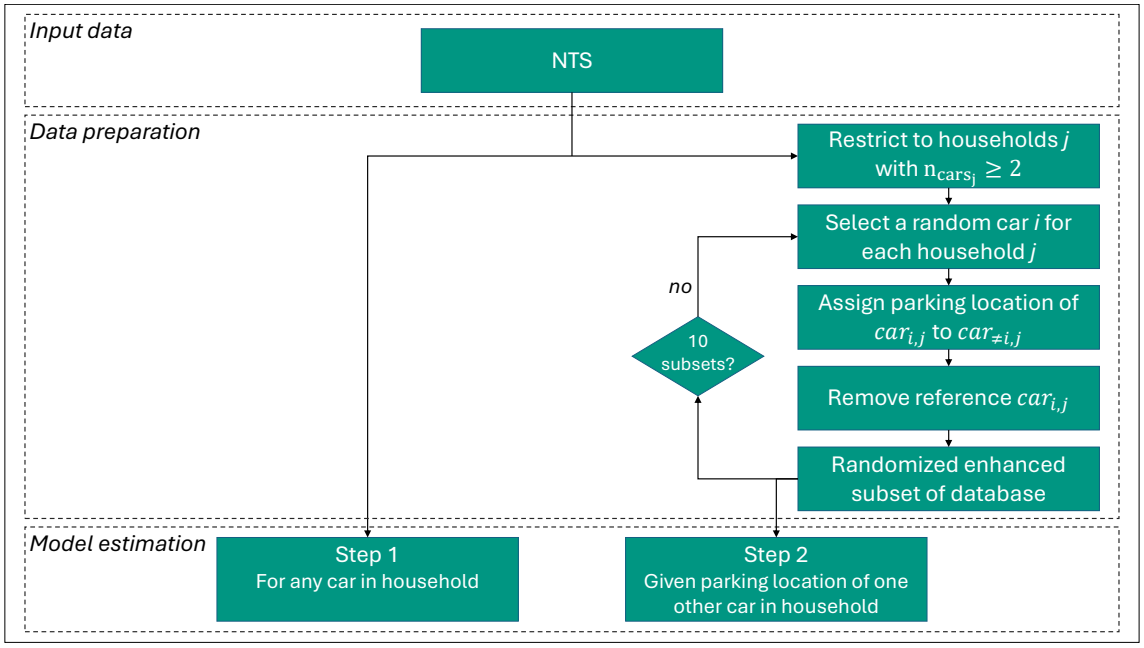


Figure 2: Flowchart illustrating the steps of data preparation and model estimation.

To account for stochastic variation, as one vehicle is selected randomly, $N = 10$ subsets are generated using different random seeds. These subsets (each comprising of 30,440 cars) are estimated separately, with the parking location of another household car as additional explanatory variable. Subsample-specific parameter estimates β_n are obtained for each replication. The final parameter $\bar{\beta}$ is calculated as mean across subsets, while total standard errors are computed according to Rubin's Rules (Rubin, 1988), comprising within-subset variance (W) and between-subset variance (B), see Equations 1–3. SE_{total} and $\bar{\beta}$ are used to determine the overall significance of the parameters.

$$W = \frac{1}{N}\sum_{n=1}^{N} SE_n^2 \tag{1}$$

$$B = \frac{1}{N-1}\sum_{n=1}^{N}(\beta_n - \bar{\beta})^2 \tag{2}$$

$$SE_{\text{total}} = \sqrt{W + \left(1 + \frac{1}{N}\right) B} \tag{3}$$

All models were estimated iteratively using the Apollo package in R (Hess & Palma, 2019). Vehicle-related attributes were introduced first, followed by household and spatial characteristics. Intra-household characteristics were added in the final modeling step.

4 Results

Vehicle, household, spatial, and intra-household characteristics all significantly influence the residential parking location, although their relative contributions to the model's explanatory power differ substantially. Figure 3 illustrates the model fit in terms of adjusted R^2 and BIC across different model specifications. Vehicle and household characteristics contribute only marginally to the explanatory power, whereas spatial characteristics and consistent intra-household parking behavior explain a substantial share of the variance.
Due to the larger sample size, Step 1 shows a better model fit when only vehicle, household, and spatial attributes are considered (adjusted R^2 of 0.19 vs. 0.16). However, this advantage is offset by intra-household characteristics, yielding an adjusted R^2 of 0.28 for the final model in Step 2. The final estimates for Steps 1 and 2 can be found in Table 1 in the Appendix.

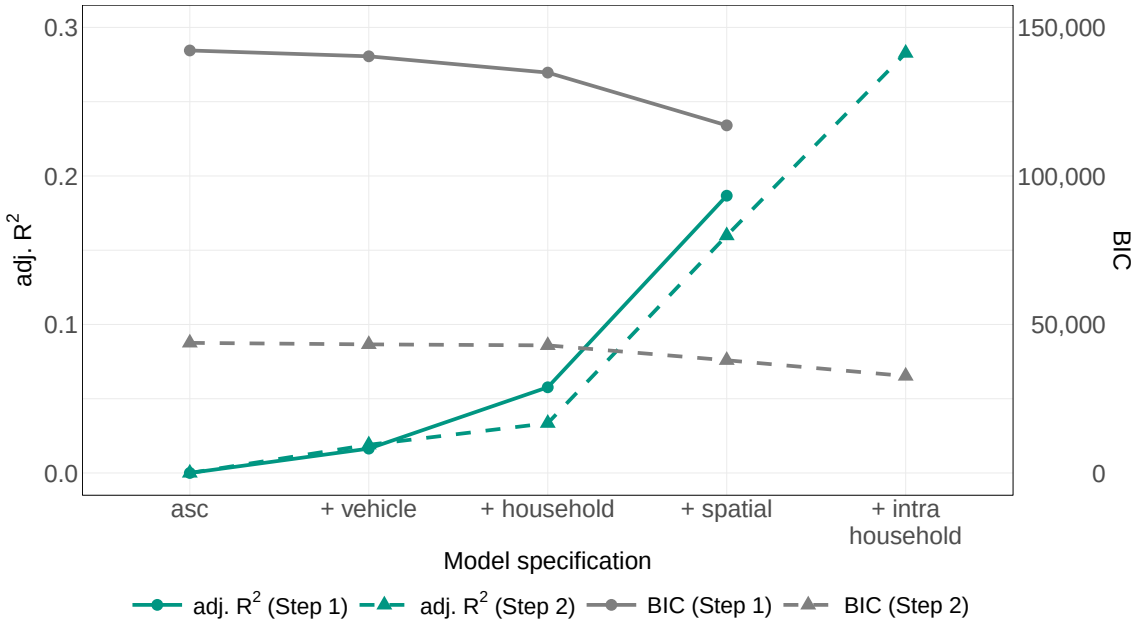


Figure 3: Model fit.

With regard to vehicle attributes, hybrid and battery electric vehicles are more frequently parked off-street than combustion vehicles. Battery electric vehicles, in particular, show a strong tendency to use private parking facilities, which is likely related to the availability of private charging infrastructure. Further, vehicles with higher annual mileage are more likely to be parked on-street rather than in public or private garages, which is also in line with existing literature. The NTS does not provide information on vehicle purchase prices. However, horsepower, vehicle class, and vehicle status suggest that more valuable cars (due to more horsepower and larger size) are more likely to be parked off-street. In contrast, company-owned vehicles are more likely to be parked on-street, which may reflect that company-owned cars are used daily for commuting and therefor should be easily accessible. Another explanation could be that safety considerations may be more pronounced for privately owned vehicles.
Household characteristics further refine the understanding of residential parking choice. Higher socioeconomic status has the strongest effect on the use of public garages and is also associated with a greater likelihood of private off-street parking and permitted on-street parking, indicating a general willingness to pay for parking. Multi-car households rely more heavily on cost-free on-street parking, as more costly alternatives such as permitted on-street parking or public off-street parking appear to be less attractive. Furthermore, larger households show a lower propensity to use public garages. The presence of minors and seniors in a household both increases the likelihood of having access to a secured off-street parking facility, with this effect being particularly pronounced for seniors. In households with unemployed members, increased price sensitivity can be observed, as cost-free on-street parking dominates.
While car- and household-related variables show significant and plausible effects, they only explain peoples behavior to a limited extent. In contrast, as one would expect, spatial factors have the greatest influence on parking behavior. In rural areas, private parking is much more likely, whereas multi-family and multi-story housing tend to encourage permitted on-street parking and private

garages. In contrast, single-family housing mainly supports private parking. High neighborhood quality is linked to permitted on-street parking and public garages, reflecting their increased availability in dense, central areas. Accessibility patterns reinforce this interpretation: paid on-street parking is concentrated in very high-density environments (5-Minute city), while the likelihood of private parking rises with increasing travel times to key points of interest. Similarly, greater distance from public transit stations corresponds with higher probabilities of private off-street parking.
When considering intra-household behavior, hence the given parking location of one other car within the household, stable results were observed across all ten iterations in the second modeling step, as shown in Figure 4. Overall, households exhibit consistent parking behavior: if one car is parked at a particular type of infrastructure, it is likely that the other household cars follow the same pattern. Only for the combination of public off-street and private off-street parking within a household could no significant estimates be obtained, which, however, appears reasonable.

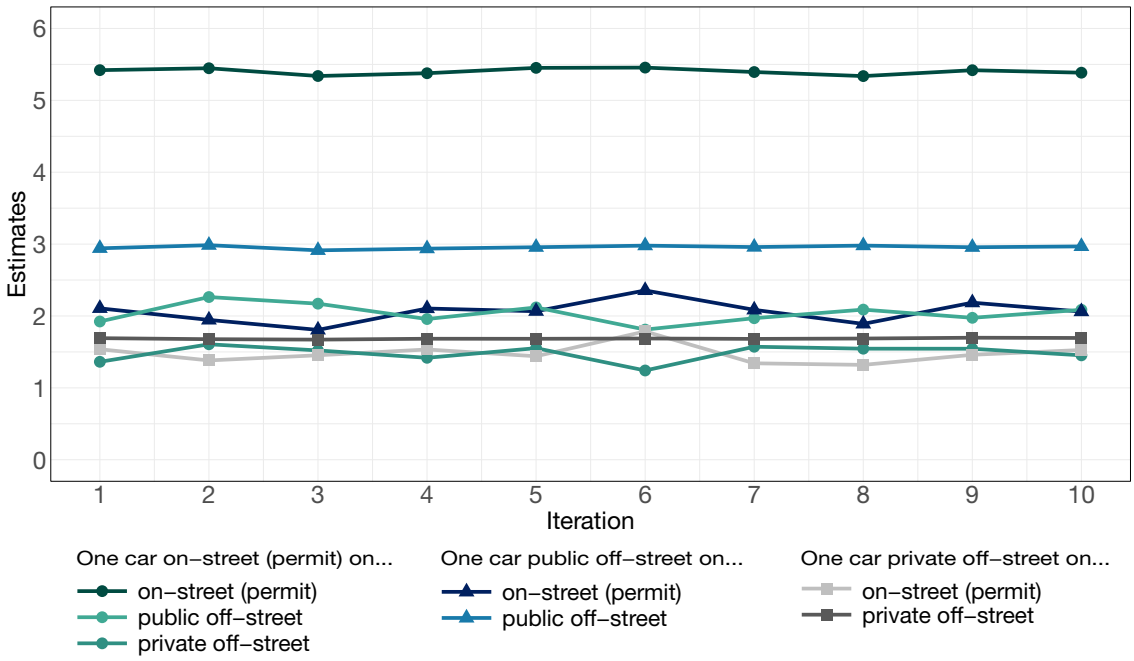


Figure 4: Variability of intra-household estimates across iterations

Furthermore, pairwise comparisons of the parameters (e.g., the influence of one household car being parked publicly off-street on another household car being parked privately off-street, and vice versa) differ by only ± 1 percentage point. Together with the stability of the parameters across all ten iterations, this suggests that the designation of a primary household vehicle plays only a minor role in obtaining reliable estimates for all subsequent vehicles.
All analyses are based on simple multinomial logit models, although multiple nesting structures were also explored. Neither an "on-street" nest (with or without permit) nor a "security" nest (public and private off-street) produces feasible nesting parameters. Only a "paying" nest (on-street with permit and public off-street) obtains a feasible, yet weak, nesting parameter, which does not improve model fit and is therefore not considered further.

5 Discussion

In this paper, we present a two-step modeling approach to identify determinants of residential parking location choice based on national travel survey data.
While incorporating intra-household characteristics in Step 2 substantially improves model fit, the second stage builds on the Step 1 model. Consequently, estimation errors from the first stage propagate into the second.
Due to the structure of the NTS, no additional spatial characteristics can be incorporated. Hence, there is no information on whether parking permits or public garages are viable options, nor on their associated costs, although both are key determinants of household decision-making. Including such variables would substantially improve the model's sensitivity to policy measures.

Although the availability of residential parking infrastructure influences both car ownership and travel behavior, the proposed approach only captures its impact on travel behavior. This limitation arises because information on parking infrastructure is collected only for households that own cars. Nevertheless, agent-based travel demand models typically do not account for residential parking location. Explicitly incorporating this dimension allows for a more realistic representation of access and egress times, as well as expected parking search time in mode choice models, thereby enhancing the behavioral realism of decision-making.
With respect to model application, we propose a two-step approach as part of the assignment of mobility tools. This approach is motivated by the superior performance of Step 1 when considering only vehicle, household, and spatial attributes, and the improved performance of Step 2 when incorporating intra-household characteristics.
Accordingly, once the number of household vehicles has been determined, the parking location of one vehicle should first be assigned. Subsequently, the parking locations of the remaining vehicles can be determined while accounting for intra-household effects.
In synthetic populations, vehicle attributes are typically not available at the level of detail used in this study. However, given their relatively limited influence, reasonable results can still be achieved by relying primarily on household and spatial characteristics.
To provide a comprehensive overview, all results are reported in Table 1. However, restricting the specification to statistically significant parameters substantially reduces the number of variables without a meaningful loss in model fit. Thus, overspecification is unlikely to be a major concern.
Lastly, permitted on-street and public off-street are only available in specific urban contexts. These options should therefore be included in the choice set only where they are realistically available.

6 Conclusions

Various factors influencing residential parking location choice were identified within a methodologically transferable framework. Among these, spatial attributes and consistent intra-household behavior provide the greatest explanatory power. Although residential parking infrastructure is closely linked to the built environment and no additional spatial variables could be incorporated, the model achieves a reasonable fit. Moreover, the results suggest that residential parking location should be integrated into agent-based travel demand models using a two-stage approach to enhance the behavioral realism of mode choice models.

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A Appendix

Table 1: Multinomial logit model for residential parking choice

	On-street (permit)		**Public off-street**		**Private off-street**	
	Step 1	**Step 2**	**Step 1**	**Step 2**	**Step 1**	**Step 2**
Constant	-1.6803***	-3.8228***	-0.9764***	-1.8406***	0.2753***	-0.3666
	(0.1784)	(0.8306)	(0.1306)	(0.4508)	(0.0866)	(0.2368)
Vehicle characteristics						
Powertrain (ref: Combustion)						
Hybrid	-0.0332	0.1339	0.3202***	0.1338	0.3523***	0.4068***
	(0.1216)	(0.3909)	(0.0746)	(0.1911)	(0.0516)	(0.1150)
Electric	0.1534	0.4835	0.3591***	0.1510	0.7037***	0.8152***
	(0.1287)	(0.3357)	(0.0819)	(0.2279)	(0.0534)	(0.1071)
Year of manufacture (ref: before 2000)						
2000–2015	-0.0862	0.3339	-0.6521***	-1.1447***	-0.3785***	-0.5697***
	(0.1190)	(0.4108)	(0.0833)	(0.1998)	(0.0580)	(0.1161)
after 2015	-0.2679*	0.2051	-0.5864***	-1.0813***	-0.3255***	-0.5176***
	(0.1370)	(0.4605)	(0.0948)	(0.2372)	(0.0653)	(0.1214)
Annual mileage in km (ref: under 10,000)						
10,000–20,000	-0.0133	0.0819	-0.2620***	-0.3377***	-0.1695***	-0.1494***
	(0.0519)	(0.1793)	(0.0368)	(0.0927)	(0.0235)	(0.0500)

Table 1 continued

	On-street (permit)		Public off-street		Private off-street	
	Step 1	**Step 2**	**Step 1**	**Step 2**	**Step 1**	**Step 2**
20,000–50,000	-0.0059	0.1211	-0.4138***	-0.4752***	-0.3186***	-0.2842***
	(0.0700)	(0.2158)	(0.0506)	(0.1285)	(0.0312)	(0.0685)
above 50,000	-0.1928	0.1462	-0.7334***	-0.9876***	-0.5249***	-0.5238***
	(0.1557)	(0.4311)	(0.1239)	(0.3282)	(0.0670)	(0.1318)
Horsepower (ref: under 100)						
100–150	0.0501	0.1351	0.4094***	0.4297***	0.3003***	0.3246***
	(0.0566)	(0.1652)	(0.0440)	(0.1453)	(0.0256)	(0.0598)
above 150	-0.0008	0.0382	0.9012***	1.0919***	0.5712***	0.6084***
	(0.0691)	(0.2007)	(0.0495)	(0.1525)	(0.0307)	(0.0666)
Vehicle class (ref: small)						
large	0.0684	0.0219	-0.0207	0.0470	0.1262***	0.1847***
	(0.0553)	(0.1668)	(0.0384)	(0.1076)	(0.0250)	(0.0547)
Vehicle status (ref: low)						
medium	0.1701*	0.1101	0.2822***	0.3676**	0.2205***	0.2884***
	(0.0712)	(0.2280)	(0.0524)	(0.1448)	(0.0327)	(0.0709)
high	0.2566*	0.0634	0.3695***	0.4433*	0.2328***	0.2689**
	(0.1145)	(0.3856)	(0.0787)	(0.2500)	(0.0508)	(0.1242)
Company car (ref: no)						
yes	-0.0604	-0.0476	-0.4035***	-0.7352***	-0.3438***	-0.4269***
	(0.0866)	(0.2309)	(0.0611)	(0.1812)	(0.0386)	(0.0894)
Household characteristics						
Economic status (ref: medium)						
very low	0.2480*		-0.5195***		-0.4861***	0.0124
	(0.1367)		(0.1310)		(0.0703)	(0.2269)
low	-0.0407	-0.1606	-0.2824***	-0.1052	-0.2026***	-0.0512
	(0.1102)	(0.6539)	(0.0900)	(0.3825)	(0.0508)	(0.1277)
high	0.1544**	-0.1603	0.4137***	0.2643	0.1794***	0.0527
	(0.0651)	(0.2364)	(0.0482)	(0.1667)	(0.0285)	(0.0630)
very high	0.3047***	-0.0372	0.7229***	0.4758***	0.3273***	0.1613**
	(0.0725)	(0.2395)	(0.0536)	(0.1816)	(0.0323)	(0.0764)
Number of cars in household (ref: one)						
two	-0.6355***		-0.7116***		-0.2425***	
	(0.0531)		(0.0391)		(0.0260)	
three or more	-0.9542***	-0.2332	-0.9262***	-0.2705**	-0.3402***	-0.0960
	(0.0922)	(0.2024)	(0.0594)	(0.1125)	(0.0351)	(0.0638)
Household size (ref: one)						
two	0.1908***	-0.0172	-0.1123**	-0.0587	0.1447***	-0.1285
	(0.0659)	(0.5250)	(0.0483)	(0.3112)	(0.0354)	(0.1781)
three	0.0147	-0.1219	-0.5321***	-0.4465	-0.0115	-0.2645
	(0.0864)	(0.6026)	(0.0643)	(0.2992)	(0.0418)	(0.1849)
four	0.1390	-0.1125	-0.7226***	-0.5606*	0.1103**	-0.1808
	(0.0940)	(0.5387)	(0.0722)	(0.3345)	(0.0437)	(0.1779)
five or more	0.0315	-0.1730	-1.1720***	-0.9941***	-0.0546	-0.3319
	(0.1348)	(0,6421)	(0.1119)	(0.3394)	(0.0561)	(0.2184)
Minor in household (ref: no)						
yes	0.0595	-0.1509	0.3677***	0.2886**	0.2009***	0.2073***
	(0.0735)	(0.2306)	(0.0549)	(0.1392)	(0.0301)	(0.0640)
Senior age +65 in household (ref: no)						
yes	-0.1453*	0.0497	0.4843***	0.0364	0.7700***	0.4503***
	(0.0880)	(0.2837)	(0.0551)	(0.1487)	(0.0365)	(0.0793)
Employed person in household (ref: no)						
yes	-0.2116***	-0.0394	-0.0538	-0.1419	-0.2231***	-0.1523**
	(0.0672)	(0.2352)	(0.0481)	(0.1490)	(0.0305)	(0.0597)
Unemployed person in household (ref: no)						
yes	-0.4230**		-0.4800***	-0.1743	-0.2434***	-0.0793
	(0.1741)		(0.1404)	(0.4930)	(0.0741)	(0.1787)

Table 1 continued

	On-street (permit)		Public off-street		Private off-street	
	Step 1	**Step 2**	**Step 1**	**Step 2**	**Step 1**	**Step 2**
Spatial characteristics						
Area type (ref: Metropoliis)						
Regiopolis and large city	0.0591	-0.0421	-0.0202	0.0780	0.4825***	0.3717***
	(0.0550)	(0.2213)	(0.0451)	(0.1481)	(0.0323)	(0.0860)
Medium-sized city in urban reg.	-0.6182***	-0.6488***	0.2671***	0.2987**	0.8671***	0.6262***
	(0.0755)	(0.2051)	(0.0455)	(0.1396)	(0.0311)	(0.0905)
Small-town area in urban reg.	0.0750	-0.1599	-0.0829	0.3566	1.2244***	0.9798***
	(0.2276)	(0.5658)	(0.1373)	(0.2879)	(0.0591)	(0.1240)
Central city in rural reg.	0.7124***	0.4186	0.0472	0.1480	0.9204***	0.7273***
	(0.0887)	(0.3394)	(0.0792)	(0.2125)	(0.0480)	(0.1151)
Medium-sized city in rural reg.	0.2474**	0.0168	0.2682***	0.3690*	1.2444***	0.9203***
	(0.1084)	(0.3214)	(0.0729)	(0.2096)	(0.0426)	(0.0879)
Small-town area in rural reg.	0.4395**	0.3245	-0.0629	0.3184	1.4039***	1.1236
	(0.1765)	(0.3448)	(0.1312)	(0.2926)	(0.0563)	(0.1355)
Building type (ref: single-family house)						
Multi-family house	1.4462***	0.9027***	0.5288***	0.4836***	-0.5990***	-0.3993***
	(0.0646)	(0.2084)	(0.0446)	(0.1261)	(0.0299)	(0.0684)
Apartment building	0.6731***	0.2393	0.5553***	0.5233*	-1.2238***	-0.8620***
	(0.1357)	(0.5359)	(0.0873)	(0.3025)	(0.0769)	(0.1961)
other	1.1886***	0.6613***	1.0011***	0.7315***	-0.2327***	-0.0901
	(0.0742)	(0.1919)	(0.0476)	(0.1688)	(0.0346)	(0.0814)
Building use (ref: private)						
Mixed-use	0.5445***	0.3292	0.5553***	0.394***	-0.0424	-0.0090
	(0.0501)	(0.2173)	(0.0386)	(0.1482)	(0.0281)	(0.0631)
Commercial	0.2663	-0.3825	0.8272***	0.5427	0.5572***	0.5076*
	(0.1991)	(0.8506)	(0.1351)	(0.4431)	(0.1056)	(0.2692)
Residential location quality (ref: low)						
medium	0.0996	-0.0866	0.3117***	0.1704	0.0139	-0.0820
	(0.0775)	(0.2742)	(0.0570)	(0.1580)	(0.0333)	(0.0896)
high	0.5578***	0.1870	0.3195***	0.1649	0.0122	-0.0929
	(0.0810)	(0.2717)	(0.0619)	(0.1690)	(0.0356)	(0.0881)
X-Minute city (ref: 5 min)						
10 min	-1.2340***	-0.8495***	-0.2869***	-0.2403*	0.1114***	0.0576
	(0.0531)	(0.2151)	(0.0435)	(0.1379)	(0.0351)	(0.1031)
15 min	-2.0844***	-1.5663***	-0.8276***	-0.5870***	0.4833***	0.3144***
	(0.1239)	(0.3116)	(0.0667)	(0.1994)	(0.0415)	(0.1072)
20 min	-1.8397***	-1.6124***	-0.8763***	-0.7424**	0.8580***	0.6184***
	(0.2164)	(0.5666)	(0.1115)	(0.3137)	(0.0541)	(0.1407)
30 min	-2.2027***	-1.8989**	-1.4226***	-1.1779***	1.0846***	0.7899***
	(0.3108)	(0.7402)	(0.1655)	(0.3751)	(0.0610)	(0.1373)
60 min	-1.2838***	-0.8375*	-0.8002***	-0.2009	1.3599***	1.1286***
	(0.2489)	(0.4850)	(0.1804)	(0.3628)	(0.0743)	(0.1605)
PT accessibility (ref: below 250 m)						
250 m - 500 m	0.1160**	0.1724	-0.0481	-0.0493	0.0717***	0.0678
	(0.0559)	(0.1507)	(0.0385)	(0.1001)	(0.0231)	(0.0537)
500 m - 1,000 m	-0.1952	-0.0767	0.0142	0.0652	0.2588***	0.2202**
	(0.1993)	(0.4729)	(0.0890)	(0.2070)	(0.0434)	(0.0954)
above 1,000 m			-0.1316	-0.2913	0.3747***	0.2752**
			(0.1915)	(0.4710)	(0.0695)	(0.1158)
Intra-household characteristics						
One car on-street (permit)		5.4028***		2.0364***		1,4816***
		(0.2520)		(0.2630)		(0.2222)
One car public off-street		2.0605***		2.9574***		0.0894
		(0.2788)		(0.1048)		(0.1175)
One car private off-street		1.4779***		0.1505		1.6851***
		(0.2410)		(0.1340)		(0.0406)

Summary Statistics	**Step 1**	**Step 2**
Observations	84,549	30,440
Adj.Rho-squared vs eq. shares	0.51	0.63
Adj.Rho-squared vs obs. shares	0.19	0.28

Rob. standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Reference category: free on-street parking.