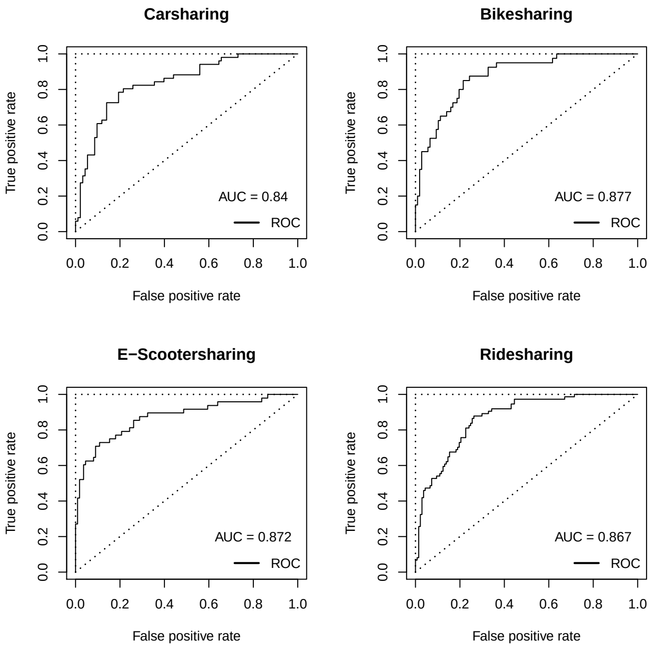

What drives the usage of shared transport services?

An impact analysis of supply and utilization of mobility services in German cities

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What drives the usage of shared transport services?

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Abstract

Shared mobility is widely discussed, yet only few travelers actually make use of shared services. Apart from personal characteristics, the supply and more specific the supply density of shared vehicles is assumed to be crucial for a widespread shared mobility usage. In this paper, we test this hypothesis. Moreover we provide insights into the impact of current mobility behavior on the usage intention for shared transport services.
For this purpose, we combine existing transport usage data with the real supply of shared vehicles in selected cities in Germany. We investigate free-floating and station-based car- and bikesharing, free-floating e-scootersharing, as well as ridesharing. To do so, we collected data on the vehicles supplied per service for beginning of 2020. In a first step, we analyze group differences in terms of intended usage between people living in cities where the services are offered and those who live in cities without access to such services. This information is used in a second step when we analyze to what extent the supply density is driving usage intention for a specific trip purpose obtained from the first analysis step. Therefore, we apply logistic regression analyses that focus on socio-demographics, the users' possession of mobility tools (e.g. driver's license, car access, transit pass), their current transport behavior and the availability of services respectively.

Keywords
Shared Mobility, Urban Mobility, Supply, Usage intention

Suggested Citation

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1 Introduction

Shared transport services are one part of the "sharing economy" (Botsman and Rogers, 2010). In this sense, they are characterized as services that simultaneously or sequentially share any kind of vehicles or services amongst a defined group of users. Moreover, they use the potentials of the so-called servitization process that also takes place in the transport industry (Smith *et al.*, 2018; Vandermerwe and Rada, 1988). Hence, past analyses arguing people would need to own private cars or other modes of transport in order to use them (Le Vine *et al.*, 2013) do not hold true anymore. For this reason, these services complement or sometimes even replace former products such as private cars. This makes them one important backbone of sustainable transport systems (Jochem *et al.*, 2017). As 32% of transport related greenhouse gas emissions in Europe can be traced back to motorized individual transport (EEA, 2018), shared transport services are one crucial component to fulfill the global climate targets (UNFCCC, 2015). This, however, makes it important to understand potential adoption processes and following usage patterns of these services. Especially because the resulting effects of shared transport services can be both positive and negative, evaluation of these is important. By doing so, it can be assessed how these effects could be steered in order to reduce the ecological footprint of passenger transport (Jalali *et al.*, 2017). Potential objectives could be shifting transport from more carbon emitting modes towards shared systems (Dalkmann and Brannigan, 2007). Therefore, this paper aims to shed light on the usage intention of the urban population in Germany towards shared transport services.

In this paper, shared transport services comprise carsharing, bikesharing, e-scootersharing and on-demand ridesharing. Carsharing and bikesharing here include both station-based as well as free-floating systems. Furthermore, bikesharing included both conventional bikes and pedelecs. E-scootersharing systems were completely free-floating systems at time of the survey (September/October 2019). On-demand ridesharing is understood as both ridehailing and ridepooling, thereby making use of the differentiation between sharing and pooling (Bösch *et al.*, 2018). Hence, it can be used as single-occupancy service but also as a pooled service with unknown people using the same vehicle.

The usage intention for the analysed services is assumed to be explained by the services' characteristics as well as user behaviors such as the access to or usage of mobility tools. By combining these two views, a broader understanding of the driving factors towards using these services can be obtained.

In the next section 2, the data used for this paper is described. Section 3 is divided into three parts: First, differences in usage intention for each service are analysed using simple t-tests. Second, the supply density and further variables explained in section 2 are added to logistic regression models for each service. These models are estimated and afterwards cross-validated by using them for predictions in test data sets. Third, simulations are used to analyse differences in usage intention for selected variables. In section 4, we summarize our findings and draw conclusions.

2 Data

The data presented and analysed within this paper stem from a survey undertaken from late September to early October 2019 (Krauss *et al.*, 2020). It was collected via an online survey by using quota sampling. Therefore, only residents of cities in Germany larger than 100,000 inhabitants were eligible for participation. The limit is based on the RegioStaR categorization of the Federal Ministry of Transport and Digital Infrastructure (BMVI, 2020). In this logic, we sampled people living in RegioStaR7 categories 71 and 72. The former refers to high-density urban areas (metropolises) whilst the latter refers to less dense urban areas (regiopolises and cities). The quotas for the region of residence (the federal states were allocated to either North, East or South in accordance with the location and number of cities of interest for this study), education (low, middle, high), and gender x age (18-29, 30-39, 40-49, 50-59, 60-69, 70+ years) were fixed based on reference values by Eurostat (Eurostat, 2011). In total N = 3,061 respondents were randomly assigned to one of the four services. Cleaning and post-processing of the data set led to the following sample sizes: For carsharing, the sample includes $n = 478$, bikesharing $n = 487$, e-scootersharing $n = 528$, and ridesharing $n = 700$ respondents. The slightly larger data set for ridesharing is mainly due to not having to exclude respondents with mobility restrictions such as sight- or motion-restrictions.

This paper draws on the socio-demographics, the mobility tool holdings, current mobility behavior as well as the usage intention towards the respective transport service.
Sociodemographics. Respondents indicated age, gender, household income, and level of education.
Residence. Respondents were also asked for the ZIP code of their home, which was used to categorize them according to RegioStaR.
Service supply density. We enriched the data set by a detailed desk research into the supply of the respective service in the cities surveyed (last updated April 2020). Therefore, we investigated whether any of the four services is provided in the cities of interest. If there was one, we searched for fleet numbers, i.e. the number of available vehicles in this city. For carsharing, we used data from the Bundesverband CarSharing e.V. (federal

association for carsharing) and extended it where necessary. For the other three services, we researched respective data by drawing on the suppliers' websites as well as newspaper articles or blog entries. In order to integrate the size of the cities, the fleet numbers were divided by the number of inhabitants in thousand.

Mobility tools. Respondents were asked whether they hold a driver's license (if not, they were not selected into the carsharing sub-sample) and whether they hold a transit pass for public transport ("yes" is indicated by 1, "no" by 0). They also indicated the degree to which they had access to a private car (scale from 1 "always" to 4 "never").

Mobility behavior. In order to factor in the usual mobility behavior of the respondents, they were also asked for the degrees to which they enjoy walking, cycling, driving a car, and using public transport (e.g. "I like to go by foot." on a scale from 1 "totally disagree" to 7 "totally agree"). They also assessed the situation for walking, cycling, driving a car, and public transport in their city (scale from 1 "very good" to 6 "insufficient").

Environmentalism. Respondents indicated the degree of their environmental concern with three statements (e.g. "Protecting the environment is an important concern to me.") on Likert-scales from 1 ("I do not agree at all.") to 5 ("I agree completely.").

Opinion about the respective transport service. Respondents indicated their global opinion about the service they were asked about on a scale from 1 ("very negative") to 7 ("very positive").

Usage intention. The usage intention towards the service was indicated by respondents to what extent they can imagine to use the service on a scale from 1 = "definitely not" to 5 = "definitely yes". For the analyses undertaken within this paper, a dichotomous variable was created that is 1 if the respondent indicated 4 = "possibly yes" or 5. If the respondent indicated 1 to 3, the usage intention is set to 0. By doing so, we aim to clearly differentiate between usage or non-usage that is closer to real-life decision-making.

3 Results

The results of this paper are structured as follows: First, the differences in usage intention for people living in cities with a respective service supply is tested against the usage intention of people living in cities with no such service. This is followed by analysing the impact of the variables explained in section 2 on the intention to use car-, bike-, e-scooter or ridesharing. This is done by running a logistic regression for each service that is calculated based on a sub-set of the data (the training data set) and cross-validating it with the remainder of the data (the test data set). Third, simulations are used in order to analyse differences towards usage intention.

3.1 Supply density

As can be seen from Table 1, the amount of e-scooters put on the streets in the autumn of 2019 has been enormous. There are more e-scooters in the larger German cities than bikes in respective sharing systems. Four cities have e-scooter numbers of above 7 per 1,000 inhabitants with Bonn leading this group (7.97 scooters/1,000 inhabitants). Bikesharing systems are well below with approximately 4 to 5 bikes per 1,000 inhabitants. Dusseldorf exhibits the highest density with 4.84 bikes. Regarding carsharing, Karlsruhe is on top of the list with a plus of more than one car over the second city Munich. This is especially remarkable as Karlsruhe is, together with Freiburg, the only city with less than one million inhabitants in this group. Ridesharing service densities are not as easy to interpret as one vehicle can transport several people at once. Hence, these numbers are substantially smaller than those of the other three services. With 0.16 vehicles per 1,000 inhabitants, Dusseldorf tops the list here. We observe that Dusseldorf has a rather large supply of the four shared transport services investigated in this survey. Berlin and Munich also offer large numbers of vehicles but interestingly this does not apply for the e-scooters. Looking at the absolute numbers, of course, Berlin tops the list with approximately 15,000 e-scooters, followed by Hamburg (8,275), Cologne (7,889) and Munich (7,313). Nevertheless, it is interesting to observe that especially larger cities but not metropolises seem to be of interest for e-scootersharing suppliers.

In a first step towards analysing the impact of supply density on usage intention of people (scale from 1 = "definitely not" to 5 = "definitely yes"), we conducted two-sided t-tests with the means of usage intention between people living in cities with supply and those

Table 1: Highest supply densities of car-, bike-, e-scooter, and ridesharing in German cities (per 1,000 inhabitants)

Carsharing		Bikesharing		E-Scootersharing		Ridesharing	
Karlsruhe:	3.23	Dusseldorf:	4.84	Bonn:	7.97	Dusseldorf:	0.16
Munich:	2.13	Frankfurt/M.:	4.38	Dusseldorf:	7.47	Hannover:	0.14
Hamburg:	1.61	Berlin:	3.84	Frankfurt/M.:	7.40	Hamburg:	0.12
Berlin:	1.60	Munich:	3.70	Cologne:	7.27	Berlin:	0.08
Freiburg:	1.59	Cologne:	3.65	Essen:	6.52	Munich:	0.06

without. The results for carsharing can be found in Table 2 from which can be seen that there are no significant differences ($p > 0.1$) in usage intention between those people living in cities with a certain level of supply density (0 or 1 car per 1,000 inhabitants). Further densities have been tested, leading to the same result.

Table 2: Difference in carsharing usage intention between cities with different levels of supply density

Mean	T-test ($df = 5$)	Mean	T-test ($df = 398$)
Supply > 0: 2.77	$t = 0.47$	Supply ≥ 1: 2.72	$t =$ -0.52
Supply $= 0$: 2.50	$p = 0.66$	Supply < 1: 2.79	$p = 0.61$

Respective results for bikesharing can be found in Table 3. No significant differences in the means of usage intention can be found between people in cities with and without any supply. However, testing the means for people living in cities with at least 1 bike per 1,000 inhabitants and the others reveals a significant difference. Those living in cities with a higher supply density exhibit a lower mean of usage intention than the others with the result being significant at the 10%-level. Yet, this effect is rather small: A supply above 1 bike per 1,000 inhabitants reveals a usage intention mean of 2.38 and the other group of 2.60. Although statistically significant ($p < 0.1$) , this in fact has if any rather low real life impacts.

Looking at the effects of e-scootersharing supply density, the respective tests can be found in Table 4. In this case, having a supply or not exposes slightly significant differences in the means of usage intention. In terms of implications, this effect becomes more interesting for a supply density of above 5: Here, people living in the higher supplied cities exhibit a

Table 3: Difference in bikesharing usage intention between cities with different levels of supply density

Mean	T-test (df =92)	Mean	T-test (df = 478)
Supply $>$ 0: 2.45	t = -1.26	Supply $\geq$ 1: 2.38	t = -1.87
Supply = 0: 2.67	p = 0.21	Supply $<$ 1: 2.60	p = 0.06

mean of 2.53 compared to the other group of only 2.19. As the scale ranges from 1 to 5, this enhances the usage intention at least from below average of the scale above this threshold. This result might explain the high values in supply density in Table 1. It is noticeable that suppliers seem to establish numbers above a certain threshold concerning the supply density. Probably, it requires a certain coverage in order to offer a seamless service. This might especially be true since e-scooters are probably more likely to be picked-up and used on the spot rather than in a planned manner. In a next step of research these numbers will be matched with single suppliers in order to generate further insights into these density thresholds.

Table 4: Difference in e-scootersharing usage intention between cities with different levels of supply density

Mean	T-test (df =297)	Mean	T-test (df = 98)
Supply $>$ 0: 2.30	t = 1.68	Supply $\geq$ 5: 2.53	t = 1.82
Supply = 0: 2.09	p = 0.09	Supply $<$ 5: 2.19	p = 0.07

When analysing ridesharing, significant differences can be found for a supply density level of above 0.05 vehicles per 1,000 inhabitants and below: Here, the mean for the higher supplied area is 2.91 whilst that for the other group is 2.72. Again, this difference does not have major practical implications although it shows that a certain level of supply density might be necessary for people to be able to imagine the usage of this service. However, these results have to be interpreted with caution as especially for ridesharing this kind of supply density might not be the crucial aspect for people to use this service. Here, an efficient algorithm of dispatching the cars within the city in order to enable short waiting times and efficient routing might be more relevant. Nevertheless, it can be shown that people can actually imagine to use this service, even in cities without supply at all (mean 2.73).

Table 5: Difference in ridesharing usage intention between cities with different levels of supply density

Mean	T-test (df =671)	Mean	T-test (df = 474)
Supply > 0: 2.86	$t = 1.35$	Supply ≥ 0.05: 2.91	$t = 1.92$
Supply $= 0$: 2.73	$p = 0.18$	Supply < 0.05: 2.72	$p = 0.06$

3.2 Regression models

In this section, the estimated logistic regression models for each transport service are presented and discussed. The models are estimated based on a 70% random sample of the respective service-specific sub-sample of the overall survey. The remaining 30% of the sample are used for cross-validation of the respective model. Thus, the sample sizes for estimating the models are $n = 334$ for carsharing, $n = 340$ for bikesharing, $n = 369$ for e-scooter- and $n = 489$ ridesharing. The binary usage intention functions as dependent variable and the independent variables were chosen according to the respective transport service. Table 6 summarizes the results. All models passed the Likelihood-ratio-test against the null-model at highest significance.
As can be seen from Table 6, the service density exhibits a significant effect for ridesharing only (5.62). The effect is positive, as expected. For the other services, the service density does not show significant impacts. Age and gender only play significant roles for carsharing whereas they do not show significant impacts on the usage intention of any of the other three services. As shown in a large number of previous studies, young males seem to have a higher usage intention towards carsharing than others. Ridesharing seems to attract more educated people than the other services. The coefficient for the lower educated group is negative whilst the coefficient for the higher income group is positive.

Regarding mobility tools and current mobility behavior, it can be seen that car access has impacts on the usage intention for e-scootersharing. For low (-1.80) and middle (-1.49) access to a private car, the usage intention is significantly lower than for the base category, i.e. not having access to a private car at all. Interestingly, in both ridesharing (0.60) and bikesharing (0.66), holding a transit pass has a positive impact on the decision whether to intend to use this service or not. For bikesharing, this might be a hint that this service might be able to function as access- and egress-mode towards the public transport as it is often discussed. For ridesharing, this might be related to the fact that ridesharing is basically a more comfortable version of public transport. The vehicles arrive on-demand and reduce access as well as egress time. The evaluation of the infrastructure for car, cycling, public transport, and walking also appear to show significant impacts: For ridesharing, a more negatively evaluated cycling infrastructure enhances the usage intention for the service (0.24). This effect holds for the evaluation of public transport and e-scootersharing as well (0.39). The opposite seems to be true for the walking infrastructure: The more negative this is evaluated, the lower the usage intention for e-scootersharing (-0.42). Enjyoing to cycle has a positive effect towards the usage intention for bikesharing (0.19). Enjoying to walk enhances the usage intention for carsharing (0.31) but reduces the usage intention for e-scootersharing (-0.30).

In order to evaluate the predictive performance of our models, we plot ROC (receiver operating characteristic) curves of the cross-validated results (from Table 6) in Figure 1. The figures as well as the calculated areas under the curve (AUC) show that the models exhibit good predictive performance. All models show a similar AUC of 0.84 to 0.88. Thus, the model predicts the outcome to a much higher level of correctness than any random model would do. This justifies further analyses.

Table 6: Logistic regression results for car-, bike-, e-scooter-, and ridesharing concerning the usage intention

Variable	Carsharing (n = 334)	Bikesharing (n = 340)	E-Scootersharing (n = 369)	Ridesharing (n = 489)
Intercept	-8.18 (1.58) ***	-5.67 (1.22) ***	-5.79 (1.95) **	-9.65 (1.33) ***
Age	-0.02 (0.01)	-0.01 (0.01) $^{\tau}$	-0.03 (0.02)	-0.01 (0.01)
Male	0.78 (0.34) *	-0.28 (0.33)	-0.38 (0.45)	0.62 (0.28) *
Income low	-0.20 (0.38)	-0.61 (0.38)	-0.87 (0.55)	0.20 (0.35)
Income high	-0.83 (0.46) $^{\tau}$	-1.03 (0.51) *	0.54 (0.44) $^{\tau}$	-0.02 (0.43)
Education low	0.39 (0.41)	-0.12 (0.44)	-0.18 (0.60)	-0.17 (0.36)
Education high	0.90 (0.41) *	0.20 (0.40)	0.05 (0.53)	0.98 (0.35) **
Driver's license	/	-0.05 (0.49)	-0.48 (0.60)	-0.01 (0.41)
Car access low	-0.16 (0.56)	0.66 (0.52)	-1.80 (0.69) **	0.35 (0.45)
Car access middle	0.03 (0.67)	0.76 (0.66)	-1.49 (0.75) *	0.31 (0.56)
Car access high	0.86 (0.81)	0.69 (0.60)	1.02 (0.77)	0.10 (0.56)
Transit pass	0.52 (0.35)	0.66 (0.35) $^{\tau}$	-0.72 (0.59)	0.60 (0.30) *
Service density	-0.08 (0.24)	0.02 (0.11)	0.09 (0.09)	5.62 (2.71) *
Environmetalism	-0.17 (0.13)	-0.17 (0.14)	0.13 (0.18)	0.09 (0.12)
Attitude service	1.33 (0.16) ***	1.12 (0.15) ***	2.10 (0.29) ***	1.50 (0.15) ***
Enjoy walking	0.31 (0.13) *	/	-0.30 (0.16) $^{\tau}$	-0.12 (0.09)
Enjoy cycling	/	0.19 (0.09) *	/	0.11 (0.07)
Evaluation car infrastructure	/	/	/	-0.15 (0.12)
Evaluation cycling infrastructure	/	/	/	0.24 (0.12) *
Evaluation public transport	/	/	0.39 (0.18) *	/
Evaluation walking infrastructure	/	/	-0.42 (0.25) $^{\tau}$	/
AIC	281.33	289.83	187.03	376.68
LLR χ^2	181.29 ***	159.23 ***	232.23 ***	295.56 ***

Variables denoted with "/" were not included in this model. Standard errors are in parentheses.
$p < 0.001$ ***, $p < 0.01$ **, $p < 0.05$ *, $p < 0.10$ $^{\tau}$

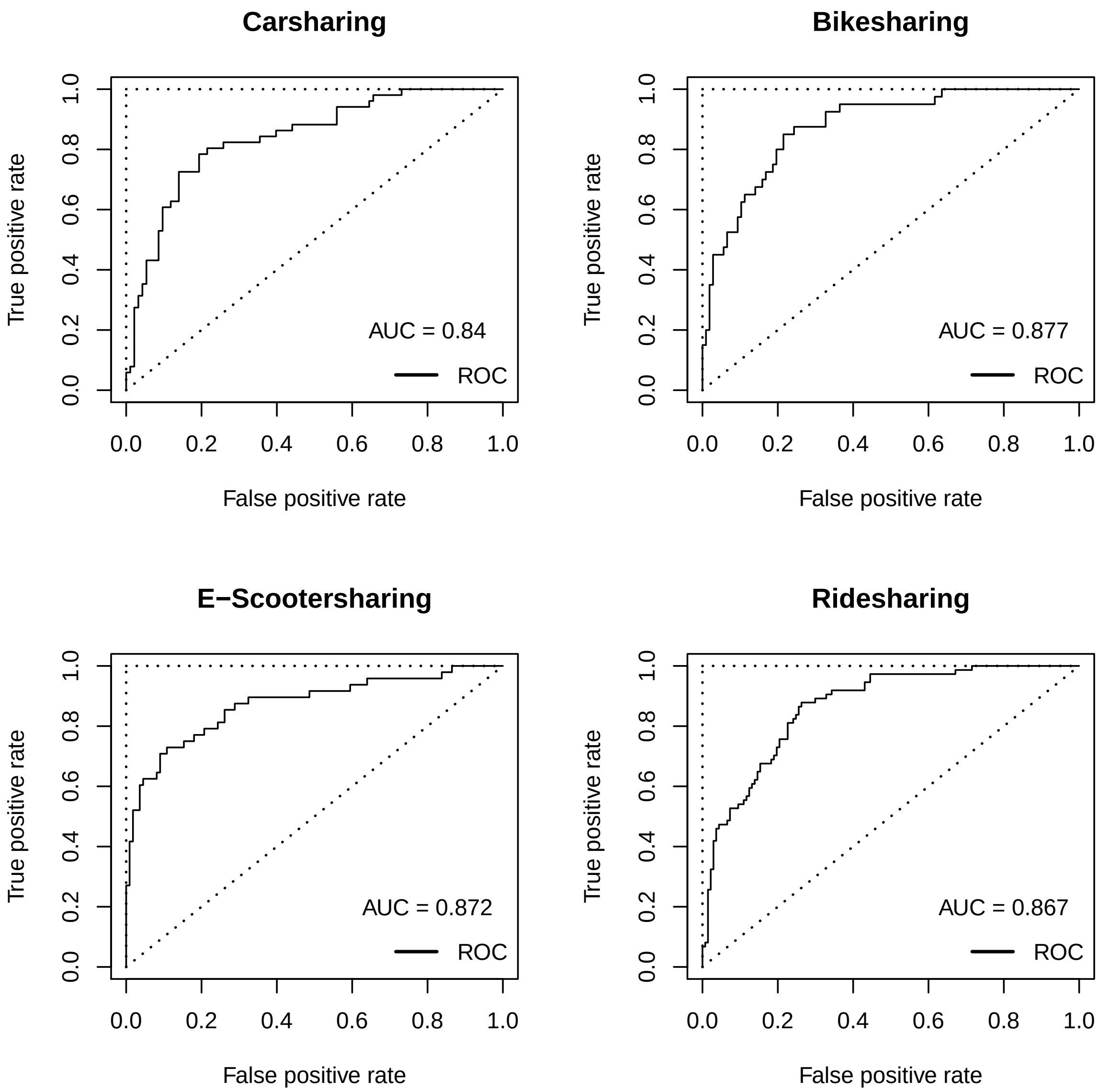
3.3 Simulated predictions of usage intention

Drawing on the models fitted and cross-validated in Section 3.2, the following analyses are based on simulations of the respective coefficients of these models. In doing so, we particularly integrate estimation uncertainty and calculate predicted probabilities. Therefore, a multivariate normal distribution around the estimated coefficients as means (with respective estimated standard error) is set up. We draw 1,500 times from this distribution. For these simulations, the complete service-specific sub-sample of the survey is applied. Estimating the probability for usage intention for each of the services based on an average case of each sample gives the results shown in Figure 2. The x-axis shows the probability for the usage intention whilst the y-axis shows the absolute frequency of each predicted probability. All services but e-scootersharing exhibit predicted probabilities for usage intention of around 0.3-0.35. E-scootersharing is below this value with 0.24. Hence, the predicted probability of intending to use the service is one quarter to one third for all transport services studied. The 95% confidence interval around the mean shows how much the predicted probabilities fluctuate. The confidence intervals are rather small.

In order to gain a broader knowledge about the current transport behavior with respect to the predicted usage intention probabilities, these are depicted in Figure 3. For car- and e-scootersharing, we assess differences of people enjoying to walk and people not enjoying to walk. For bikesharing, the differentiation is made based on whether people enjoy to cycle or not. For ridesharing, the difference is based on whether people hold a transit pass for public transport or not. In doing so, we want to find out how these mobility behavior patterns affect the predicted usage intention for the urban population in Germany. By that, potential implications for transport planning can be drawn. For all these groups of comparison, first differences are calculated to see how these "transport backgrounds" impact the usage intention for the four services.

For carsharing, this first difference (difference of value for scale-point = 1 to scale-point = 7) is negative on the 95% significance level. For e-scootersharing, it is not. However, more interestingly, the differences show different signs: For carsharing, people enjoying to go by foot exhibit a higher predicted probability to use carsharing than those not enjoying to walk. The opposite holds true for e-scootersharing: Here, people enjoying to walk show a lower predicted probability to intend to use this service than those people not enjoying to walk. For bikesharing, people who enjoy cycling exhibit a significantly higher intention to use this service than people not enjoying to cycle. In the case of ridesharing, it can be seen that people holding a transit pass exhibit a higher predicted probability for

Figure 1: Cross-validation of logistic regression models.



intending to use the service than people not holding a transit pass (difference of value for not holding a transit pass to holding a transit pass).

As can be seen from these analyses, current transport behavior affects the different transport services rather differently, which underlines the importance to thoroughly research each service on its own rather than trying to analyse them as "one" shared mobility.

Figure 2: Simulated predicted probabilities for average case (solid lines indicate the mean, dashed lines the mean +/- standard error).

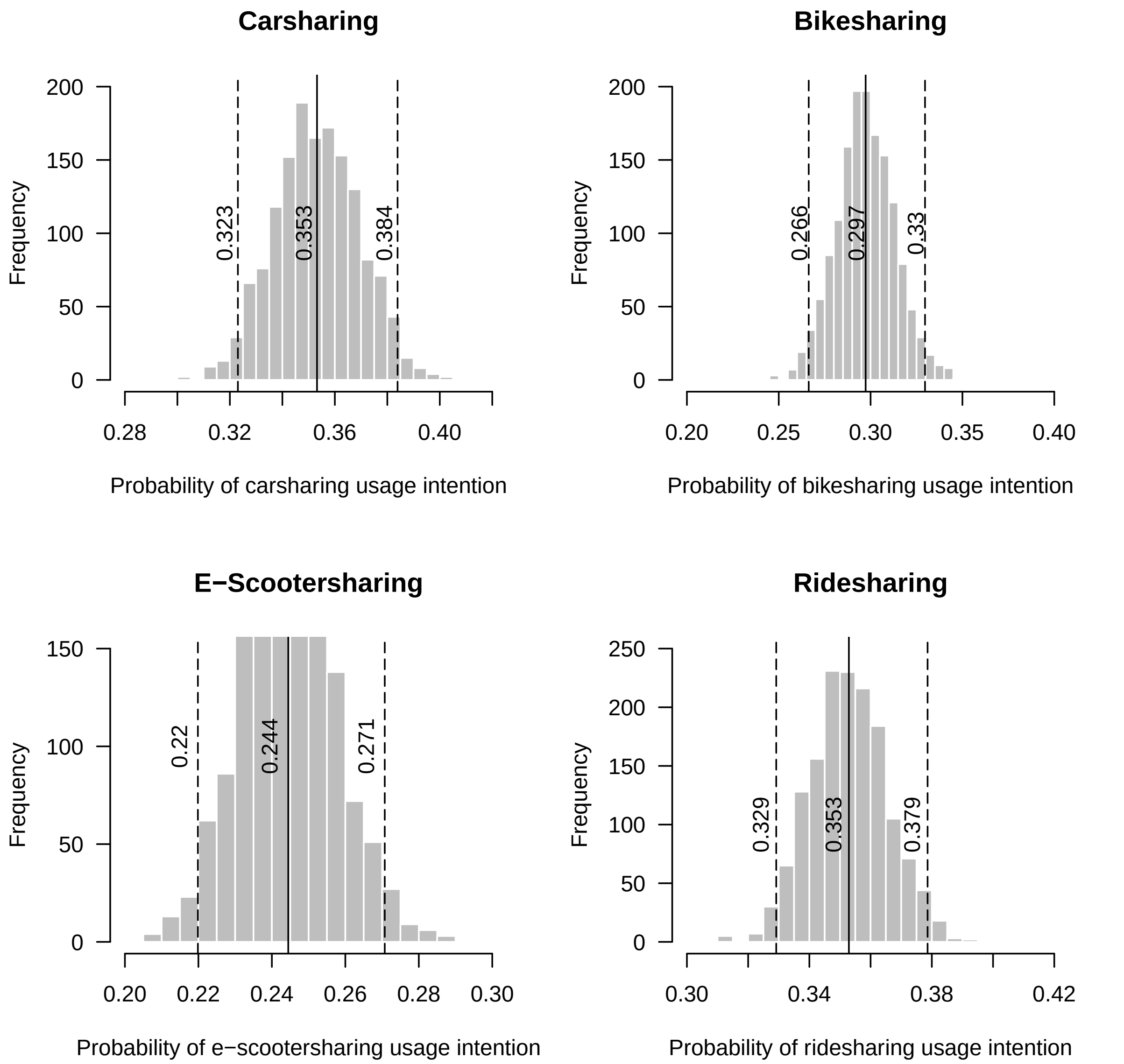
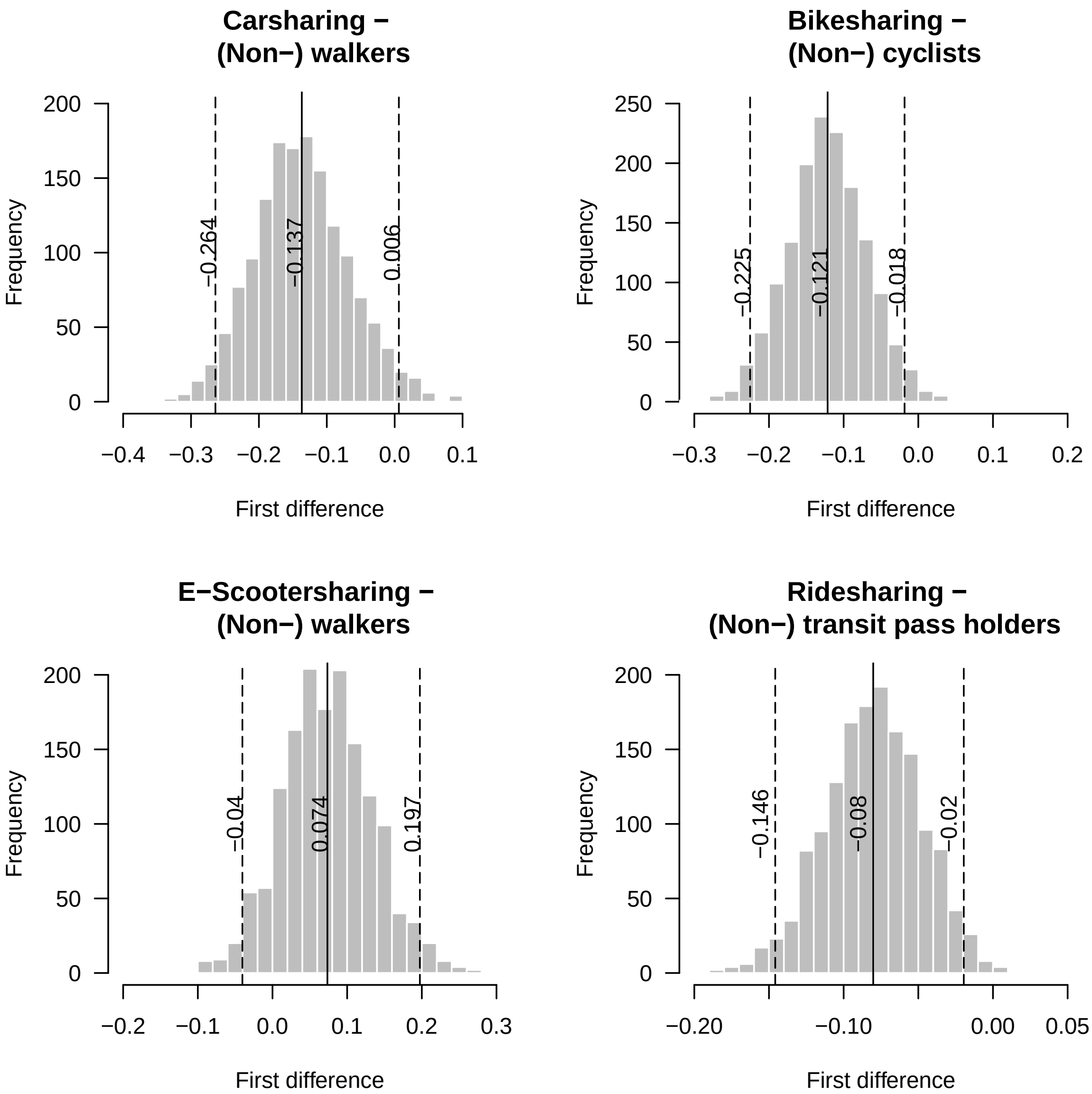
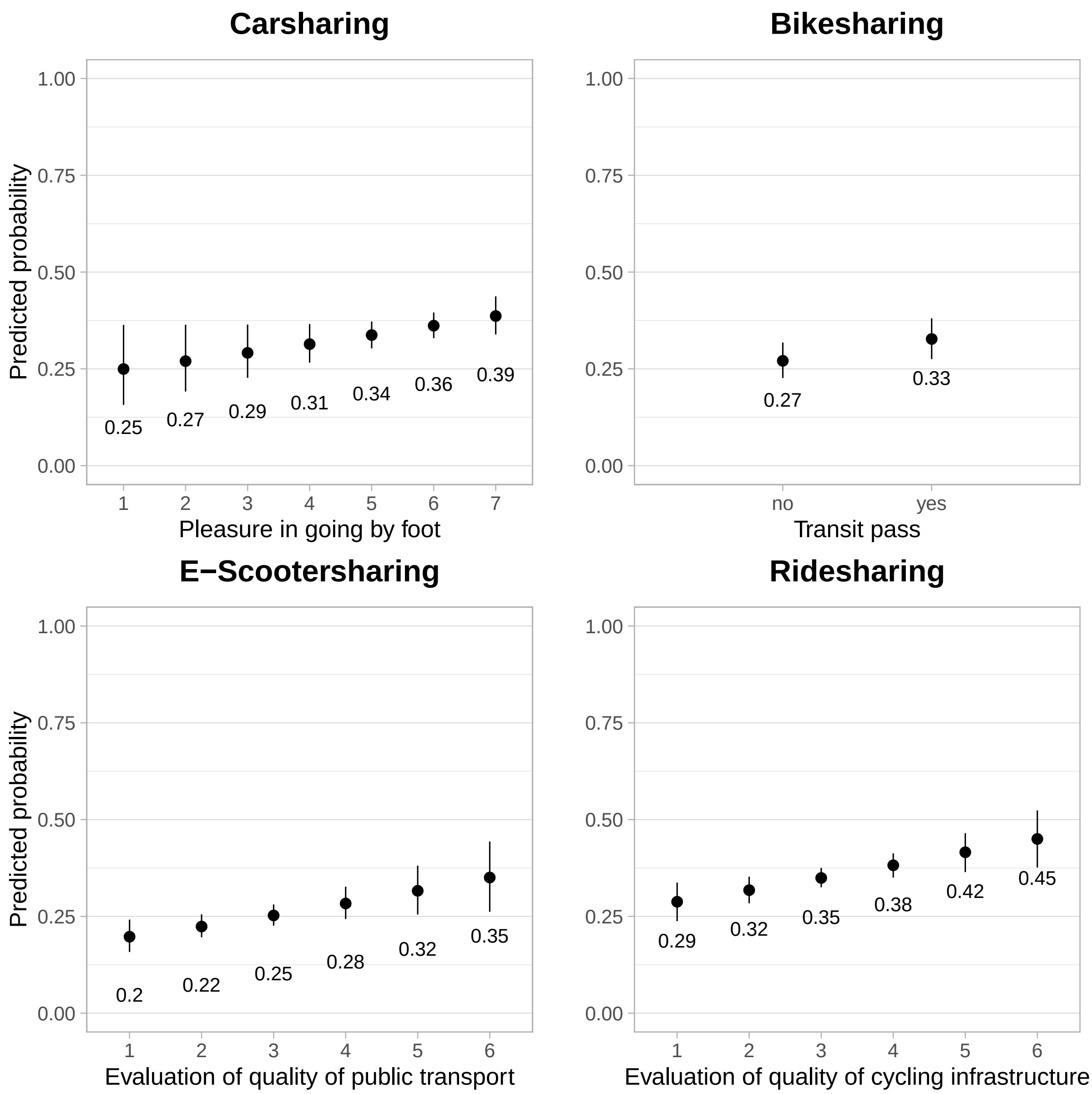


Figure 3: First differences of usage intention for specific current transport behavior (solid lines indicate the mean, dashed lines the mean +/- standard error).



From Figure 4 predicted probabilities of selected variables can be obtained by each point on the respective measurement scale. The variables are selected based on the regression results in Table 6. As shown for carsharing previously, with increasing pleasure for going by foot, the predicted probability for carsharing also increases. For bikesharing, it can be seen that holding a transit pass enhances the predicted probability for the usage intention (0.33 compared to 0.27). Although a rather small effect, this difference is significant at the 10%-level. As discussed above, this might be a hint towards the integrating effect of bikesharing for public transport services. E-scootersharing is predicted to show higher usage intention values with more negative evaluations of public transport. This could be

Figure 4: Predicted usage intention for selected variables.



interpreted as the e-scooters to fill time- and spatial-related supply gaps in the public transport system for which the e-scooter might be a good and easy to access alternative. In the case of ridesharing, the predicted usage intention increases with a more negative evaluation of the cycling infrastructure. Here, ridesharing might be the comfortable alternative to cycling if roads are not safe or no bike lanes exist.

4 Conclusion

This paper investigates the effect of supply densities of shared transport services as well as people's current transport behavior towards the usage intention for the four shared transport services car-, bike-, e-scooter-, and ridesharing. It is found that the supply density per se does not significantly impact the usage intention or predicted probability therefore. Thus, simply increasing the supply of shared mobility does not lead to increasing user numbers or usage intensities. However, it is found that current transport behavior patterns such as whether a person enjoys walking or cycling, does influence the predicted probabilities for usage intention. Moreover, it can be shown that the existing infrastructure for cycling, public transport, and walking triggers potential usage intention. Furthermore, it can be shown that the models applied within this paper are well-suited to predict the usage intention for the respective service. For an average case in the data set the predicted probability for intending to use one of the services ranges between one quarter and one third. This is by far more than current transport data reveal about actual usage of these services. This survey is limited by asking for usage intention, which is only one first step towards actually using the service. Moreover, the analyses are limited by calculating the service densities based on the total population of the cities. However, the service areas are often smaller than the city areas which might lead to distorted service densities for the actual usage within the city. In future studies, the effects of the variables shown here will be evaluated in more detail. Especially, the prediction models are to be developed in more detail in order to be able to generate higher prediction rates. Furthermore, the prediction models will be applied to bigger transport behavior data sets in Germany such as the "Mobilität in Deutschland" or "Mobilitätspanel". In another future step of research, it will be analysed which attributes are most important for mode choice amongst the services studied here. Therefor, this paper serves as a basis.

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5 References

BMVI (2020) Regionalstatistische Raumtypologie (RegioStaR). https://www.bmvi.de/SharedDocs/DE/Artikel/G/regionalstatistische-raumtypologie.htm, accessed 20.05.2020.

Bösch, P. M., F. Becker, H. Becker and K. W. Axhausen (2018) Cost-based analysis of autonomous mobility services, *Transport Policy*, **64**, 76–91.

Botsman, R. and R. Rogers (2010) *What's Mine Is Yours: The Rise of Collaborative Consumption*, Harper Business, New York, NY.

Dalkmann, H. and C. Brannigan (2007) *Transport and Climate Change: Module 5e: Sustainable Transport: A Sourcebook for Policy-makers in Developing Cities*, Eschborn.

EEA (2018) Greenhouse gas emissions from transport. https://www.eea.europa.eu/data-and-maps/indicators/transport-emissions-of-greenhouse-gases/transport-emissions-of-greenhouse-gases-11, accessed at 20.05.2020.

Eurostat (2011) Census data germany - census 2011. https://ec.europa.eu/CensusHub2/query.do?step=selectHyperCubeqhc=false, accessed 20.05.2020.

Jalali, R., S. Koohi-Fayegh, K. El-Khatib, D. Hoornweg and H. Li (2017) Investigating the Potential of Ridesharing to Reduce Vehicle Emissions, *Urban Planning*, **2** (2) 26–40.

Jochem, P., J. J. Gómez Vilchez, A. Ensslen, J. Schäuble and W. Fichtner (2017) Methods for forecasting the market penetration of electric drivetrains in the passenger car market, *Transport Reviews*, **38** (3) 322–348.

Krauss, K., A. Scherrer, U. Burghard, J. Schuler, A. Burger and C. Doll (2020) Sharing Economy in der Mobilität: Potenzielle Nutzung und AKzeptanz geteilter Mobilitätsdienste in urbanen Räumen in Deutschland, (No. S 06/2020).

Le Vine, S., M. Lee-Gosselin, A. Sivakumar and J. Polak (2013) A new concept of accessibility to personal activities: Development of theory and application to an empirical study of mobility resource holdings, *Journal of Transport Geography*, **31**, 1–10.

Smith, G., J. Sochor and I. M. Karlsson (2018) Mobility as a Service: Development scenarios and implications for public transport, *Research in Transportation Economics*, **69**, 592–599.

UNFCCC (2015) Adoption of the Paris Agreement. https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement, accessed 20.05.2020.

Vandermerwe, S. and J. Rada (1988) Servitization of Business: Adding Value by Adding Services, *European Management Journal*, **6** (4) 314–324.