Explanatory Variables For The Varying Demand Of Free-Floating Carsharing

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***Abstract*—The carsharing market changed in 2009 with the start of the free-floating carsharing system. In this kind of carsharing system the vehicle does not need to be returned to a fix station after rental but can be parked in every place of a defined operating area.**
This work focuses on the explanation of the varying demand of these carsharing systems. To understand why cars of the fleet are more demanded at a certain time, possible influence factors shall be analyzed. The base of the approach is booking data of a carsharing operator in Berlin and Munich.
The first part of this analysis consists of collecting general information about how the system works. Expert interviews with the fleet manager and other researchers as well as own analyses give a first impression of well-working areas. It turns out that CS is mainly used in areas close to the city or district center. At the end of this first stage, the following factors were chosen to be analyzed for their impact on carsharing: socio-demographic factors, political tendencies of the citizens, parking restrictions in a district and weather conditions.
The kind of parking restriction in a district of a city does not have a significant impact on the demand of carsharing vehicles. Rainy or cold weather let only the number of bookings of heavy users increase. A significant positive impact is however measurable in districts with a high percentage of electors of ecologic or liberal parties. The regression with socio-demographic data shows a positive influence of a high density of bars and restaurants and medium-sized enterprises on the number of carsharing bookings.

I. Introduction

In 2009, car2go started a new kind of carsharing system, called free-floating carsharing. Rental cars are not positioned at a fix station but can be rented at any place of a defined operating area. Via a mobile application the user can find the location of available cars and open them with his customer card. For the purposes of this paper FFCS is going to be used as an abbreviation for free-floating carsharing.
This work focuses on the explanation of the varying demand of these FFCS systems. To understand why cars of the fleet are more demanded at a certain time, possible influence factors shall be analyzed. The base of the approach is booking data of a carsharing operator in Berlin and Munich. Two data sets are used for this study: One contains data from November 2011 until October 2012 (data set 1), one from January 2013 until December 2013 (data set 2). The first data set contains booking of heavy users only. The heavy user data set is defined as the data set that includes 80% of all bookings done by the most frequent customers.

This study is split in two parts. In the beginning, the reader gets an overview over the results of different expert interviews conducted with the fleet manager and other research fellows about possible influence factors on the demand of FFCS. In addition, current research works focused on the explanation of the usage of different carsharing systems in Europe and North America are taken into account. Based on these insights, the uttered expert impressions are evaluated regarding the way they can be quantified. In the second part, those quantified data are proved concerning their effect they have on the temporarily and spatially varying booking demand.

II. Identifying external variables

The work is carried out within the project "WiMobil" that analyzes the effects of carsharing systems on the environment and traffic in the case cities Berlin and Munich. The good cooperation with the carsharing operator *DriveNow* within this project allows a direct access to booking data that make this work unique.

A. Literature review

In literature, most works about modeling the demand of carsharing are based on surveys with the purpose to find significant variables that play a role for the decision to use a carsharing vehicle. Another often used method to get booking data is by accessing and reading the API (application programming interface) of the FFCS operator. The interface is normally used by smartphone applications and websites to provide the current distribution of available cars of his fleet. Capturing booking data via API seems to provide an exact image of real bookings but it should be treated with caution. In a study by Brockmeyer et al. ([1]) booking data of FFCS operators in Berlin were collected by this method. Since they could only observe if a vehicle was available or not they could not distinguish if it was a service or a customer trip. It is supposed that their calculated trip duration is longer than the one with the original data set. But instead of the temporal use of a vehicle of around 3-4 hours they observed a time of 62 minutes. That means in consequence that data captured via API can be thrown into great errors. Nevertheless, they should not be regarded completely useless. Other studies like [21] took these data to measure the influence of particular point of interests (POI) on the number of bookings. Their approach is the zero-inflated Poisson regression. As base grid Wagner et al. use squares with an edge of 100 meters. Bookings as the dependent variable of the model are aggregated per cell as well as several POIs they take into consideration as independent variables. The zero-inflated model design exclude those cells which does not show any booking such as parks or other parking prohibited areas. The significant variables with a positive influence on the number of bookings are e.g. bars, (take-away) restaurants, the airport and areas with citizens that earn less than 500 € per month. A negative correlation was however observed e.g. in regions with a high educated population. Some factors like the income and education are very peculiar regarding their tendency because customer surveys in the project WiMobil ([10]) identified well educated men that are in average 33 years old as typical users.

Among other studies Cervero's characterization of station-based carsharing users from 2001 ([3]) and 2002 ([4]) with the help of surveys is one of the most famous works. More than 62% of the respondents were female, the average yearly income was about 50 000 $. The study also found out that the analyzed carsharing system was mainly used during afternoon peak times for non-work purposes. An interesting result is the kind of household the users live: One third of them lived alone and every fourth shared their home with non-related adults. Cervero called them the "non-traditional" households. Although his works focus on the US market and station-based systems the kind of variables he considers seem to be helpful to draw a picture of a carsharing user.

Morency et al. also identified in [13] gender and age as significant impact variables on the carsharing behavior. Moreover, the user behavior in the previous four months directly influences the current usage frequency.

In another study by Celsor and Millard-Ball ([2]) that is based on [11] the authors emphasize the importance of the neighborhoods. They summarized the results from other researchers in four factors: parking pressure, the ability to live without a car, high population density and a mix of use of a district. Some of the points will also be considered in this study.

A study from Prettenthaler in Graz ([16]) from 1999 shows the young age of the users, too. 85% of the respondents were between 25 and 44 years old. Since the study is some years old it is questionable if this distribution of age is still valid for current systems. But next to the age the education and the environmental awareness of the customers seem to have a significant influence on the frequency of use.

Stillwater et al. analyzed in [20] moreover the dependency of public transport on carsharing. Whereas the neighborhood of a lightrail station have a positive impact on the demand of carsharing regional rail availability decreases the number of bookings.

The first work that also analyzed FFCS systems is done by Kortum and Machemehl in 2012. The evaluated data of car2go in Austin show a high acceptance and use of the system in areas with a high population density (that is not very surprising) or a high percentage of students or government workers. The last factors stems from the fact that many governmental agencies contract with the operator to reduce their own vehicle fleet.

A well-written comprehensive literature review about carsharing demand estimation is published by Jorge and Correia ([8]).

B. External factors

In this study the identified significant variables from other researchers shall be considered concerning their availability for the city of Berlin and Munich. Most of them are socio-demographic and land-use data. Some studies mentioned that the attitude of people like the environmental awareness plays a role. These factors are hard to compare with the booking demand. The political tendency of someone may describe his environmental consciousness though. The parking pressure is also an influence that is hard to measure without detailed information about the parking search traffic. However, for the case of Munich the booking frequency shall be set in correlation with the kind of parking restriction that is valid at the location where the trip ends. An additional potentially influencing factor which is not spatial but temporal is the weather. It is not mentioned in the studies above but by the fleet manager that bad weather conditions changes the demand for FFCS.

It shall be mentioned that in this work the terms "demand" and "frequency" are used synonymously. The authors are aware that there might be a theoretical demand that exist but is not fulfilled because of a lack of vehicles in a particular. To identify this demand more data like information about the location of app inquiries would be necessary. To see the number of bookings as the real demand is hence a way of reducing the complexity of the problem.

1) Socio-demographic data: The socio-demographic data this work rests on are provided by infas geodaten from 2012. The geographical grid they used for aggregation is based on official distinction of the Federal Agency for Cartography and Geodesy. Different kinds of these "Kreisgemeindeschlüssel" (KGS, "county-borough code") exist in different precision. The data for this work are based on KGS22 that is described by the provider as follows:

> The "district grid" (KGS22) is introduced in the official classification as a subunit. It originally comes from areal units comprised of polling districts with 400 households in average that have a maximum of homogeneity. (cited from [15])

The operating area of the FFCS operator contains 1863 districts in Berlin and 982 in Munich with a mean area of 0.22 sqm and 0.18 sqm, respectively. To get an impression of the grid the reader may take a look to Fig. 1 which is based on this division of the operating area. Every of this cells contain information about important factors of the population and land-use, e.g.

- citizen data
  - % gender
  - % age (categories)
  - purchasing power
- household data
  - % with 1,2 or 3 and more children
  - % single, yuppies (young urban professionals), DINKS (double income no kids)
- number of companies
  - # services
  - # hotels

- miscellaneous
  - rent [per sqm]
  - private car density

Before explaining the regression model that is used to figure out the relation between the variables and the booking frequency one should presented another quantity that is will be modeled the same way.

2) Political tendency: In some talks and interviews experts gave their impression that the political tendency of the user must have a significant influence on the attitude towards FFCS and thus on the frequency of the use of the vehicles. The idea of carsharing arose among other things from an ecological motive in the last century ([19]). It is well-known that users of station-based carsharing participate in the system for environmental reasons. At political elections they are supposed to give their vote to parties which attach importance to sustainability. The political background of a FFCS user is however unknown.
In our study there are no data available about the residence of the customer. Taking results of a political election into account may thus not seem reasonable since a comparison with the customers' residence cannot be analyzed. However, this study will set these data in correlation with the number of bookings in polling districts. The motivation to treat the place of start of a booking like the place of residence of a customer comes from an evaluation done by Seign ([18], p. 43). Due to the good collaboration with the operator he got access to the customers' private addresses and analyzed the relation between the home addresses and booking starts and ends.
The graphical results shown in Fig. 1 makes clear that hot spots of bookings starts comply with a high density of the customers' residence. Seign was even able to calculate the strong relation between those quantities: 61,1% of bookings start and end within a distance of less than 500 meters. Kortum and Machemehl also analyzed the home addresses of the customers ([9], p. 8). Car2go members in Austin are distributed over the city according to the population density that is again linked to the booking demand.

In this work the results for the most important parties of the nationwide parliamentary elections in October 2013 (Bundestagswahl) are taken as independent variable in a linear regression with number of bookings as dependent variable. To measure the influence of the each variable independently of the other ones the linear model includes just the result of one party.

The socio-demographic data are treated the same way. But additionally, the authors apply the stepwise linear regression method to these data. By this, the most important of the 196 variables can easily be identified and compared for both cities.
The two models - both the simple OLS and stepwise linear regression model - assume a linear relationship between the independent and the dependent variable. That will not be valid for every variable. The necessary homogeneity of the model will probably also fail for some factors.
The reason why the authors still choose the method of

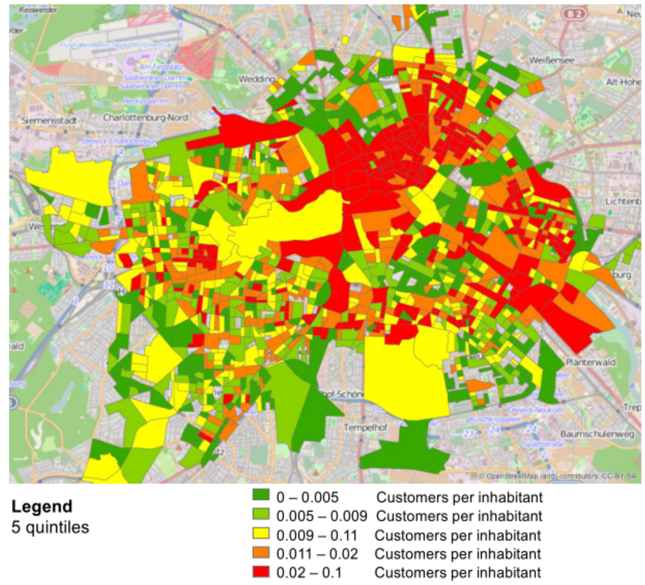

Fig. 1. Customer addresses: Customer per inhabitant in Berlin, cited from [18], p.43

Ordinary Least Squares (OLS) and stepwise linear regression is that the models are helpful to figure out general trend variables.
The simple OLS model is important to identify the contribution of every single variable for the explanation of the booking demand. By this, there is moreover a comparison of the influence of different variables possible.
The second model will take more than one independent variable into account with the purpose to find an easy model that can be used as a rough prediction of the booking demand for other cities.
The difference to an OLS model with the integration of the most important variables (regarding their single contribution) is that the correlation between two influencing variables will be regarded as well. So if for instance the income and the education would have a high impact on the booking demand, it is not probable that both variables will also be taken in a stepwise linear regression model since these two variables are supposed to be highly correlated. If the income would be already be contained in the model the education would not provide much more additional explanation.

3) Parking restrictions: Municipalities expect one main improvement of the FFCS system: They hope the parking pressure decreases in areas with a good supply of FFCS because of the abolition of private cars in the households of the users.
Parking pressure depends on the number of parking lots and the demand for parking availabilities. The car-ownership rate and the percentage of passengers arriving by car influence this demand.
FFCS can change both quantities. But one has to discuss two issues: The demand for FFCS measured by the number of bookings in an area cannot quantify this change. A higher demand may imply a high number of residents who abolished their private car as well as an increasing number of passengers arriving via car (i.e. an equal parking pressure). The second

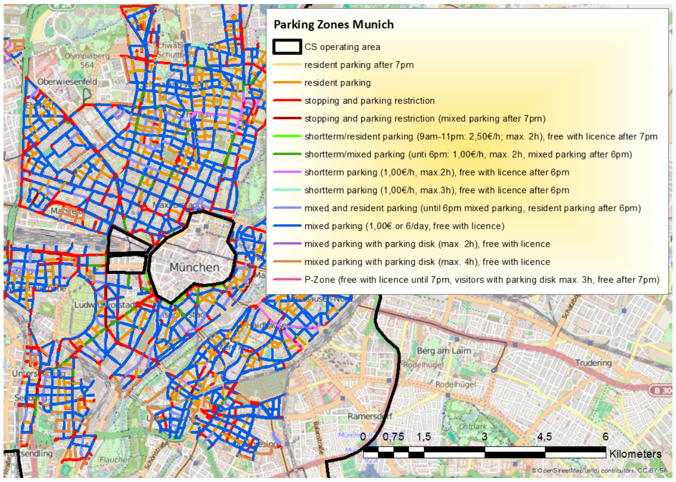

Fig. 2. Parking zones in Munich

critical point is that parking pressure is hard to measure. Even if there is no parking lot available it does not mean in consequence a high parking pressure. It may also indicate a balance between demand and supply of parking space. Moreover, parking pressure is highly dependent of the day time. An approach to measure parking pressure was done by Montini et al. in [12] via GPS tracking of some people and hence identify parking search traffic.

Nevertheless, for the city of Munich there exists one opportunity to get an indicator for a high demand for parking facilities. In 2006, the city council decided to institute a parking management system in almost all central districts. 62 parking areas were introduced with the main purpose to reserve existing publicly available parking space for residents. Next to the establishment of these areas every street (and even street side) was assigned to one of the 13 different parking zones. The distinction of the streets is shown in Fig. 2 and can be summarized by

- resident parking: residential areas with a low percentage of shopping facilities. Citizens are allowed to buy only one parking license per car that is valid in the parking area the holder lives,
- short-term parking: business and commercial areas of the city that have a high flow of customers,
- mixed parking: areas with a need of parking space for residents during the night and a high fluctuation of customers during the day.

The decision process of assigning the streets to a particular parking was a complex but very democratic and transparent procedure that is described in [7]. In short, the parking pressure was just one indicator for a parking zone. Nevertheless, it is a presumption for establishing parking regulations. The reason for this is a law in Germany that allows parking fees only in areas with a considerable lack of parking space (see German Road Traffic Act [6], 45, Art. 1b No. 2a). Next to that objective demand for parking space discussions with residents and shop owners also played a key role in the process. Thus, our approach of assigning the booking to a particular parking zone only measures a correlation to a parking zone, but not directly to the parking pressure.

Although, the wished relation between FFCS demand and parking pressure cannot be indicated, the analysis can show a preference for a particular kind of parking.

It shall be mentioned that the FFCS customers does not pay any fee for parking. The carsharing operator acquires licenses for every car that are valid in every parking area. The costs for this general license is much higher than the 30 €a resident pays for his license that is valid in only one parking area. Nonetheless, the vehicles of the fleet are not allowed to park in resident parking zones and they have to follow the regularities of shortterm parking in the same way as other car owners. If the user finishes his trip in such a parking zone he is responsible that the time restriction is complied. Without a ticket in the front window it is however difficult to determine how long the car has been parked at that place.

4) Weather conditions: One further impression of the fleet manager was that the number of bookings increases when the weather turns ”bad”. The relevance of weather effects on traffic is indubitably apparent. Eugster considers in his diploma thesis ([5]) time durations of indoor and outdoor activities and what kind of transport mode people used to reach their activity. The used weather data were not very detailed: He only calculated with average day values e.g. for temperature and precipitation. These variables got an influence on the kind of activity whereas the use of motorized individual transport was not significantly dependent on the weather. The most challenging part is to find an objective description of the subjective terminology ”bad weather”. To the authors' best knowledge there has been no official definition yet.

With the help of the variables temperature, precipitation and wind force provided by the German Weather Service an attempt is made to categorize the respective weather condition. The presumption is that FFCS vehicle becomes more attractive for the customer when it is cold, rainy or windy.

III. Analyzing External Variables

A. Influencing variables

1) Social demographics: The available socio-demographic and land use data consist of numerous detailed variables including e.g. age, income, number of companies etc. In Table I all variables that have an absolute t-statistics of more than 10 are listed. The sign of the t-statistics shows if the influence of the variable is positive or negative.

It is quite apparent that the explained percentage by some variables is higher in Berlin. In Munich, the number of certain companies such as government agencies and administrative offices have the biggest impact on booking demand. In Berlin, the number of services with around 100 employees is moreover highly correlated with the target variable. Since the customers are not supposed to go to the administration agencies in most of their trips this variable can be regarded as a representative for a good location in the city that is in most cases easily reached by public transport and a meeting point for day-time activities. The services are however a summary of very different companies that have direct contact to customers. It is clear that these places are hence also often visited and an attractive spot for terminating a carsharing

	Berlin		Munich	
	t	adj.R^2	t	adj.R^2
citizen data				
# citizens per sqm	-12.05	0.08		
type of telecommunication: classical fixed network user (index)	-10.69	0.07		
company car driver (index)	18.42	0.18	10.34	0.10
affinity to leased private cars (index)	13.80	0.11		
frequent drivers (index)	16.89	0.15		
environmental affinity (index)	12.02	0.09		
household data				
# buildings	19.05	0.18		
% buildings (best quality)	14.12	0.11		
rent	22.02	0.23		
rent (index)	22.02	0.23		
% private cars (business)	12.78	0.09	12.62	0.14
% private cars (private)	-12.78	0.09	-12.88	0.14
number of companies				
# government agencies and administrative offices	38.56	0.49	18.89	0.27
big	28.55	0.30	14.05	0.17
medium	35.75	0.43	20.04	0.29
small	34.40	0.30		
# medical surgeries	12.94	0.45		
small	12.96	0.10		
# car dealers and car repair shops	10.55	0.07		
medium	12.37	0.09		
# banks	35.53	0.45	11.60	0.12
big	15.04	0.13		
medium	35.17	0.44	11.16	0.11
small	30.83	0.38	11.46	0.12
# services	39.18	0.49	18.36	0.26
big	28.54	0.34	11.65	0.12
medium	40.46	0.51	18.92	0.27
small	35.36	0.44	16.48	0.22
# retail	23.40	0.26		
medium	22.47	0.24		
small	21.60	0.23		
# hotels	34.65	0.43	10.92	0.11
big	23.06	0.25		
medium	28.73	0.34		
small	32.75	0.40	10.68	0.10
# mechanics	20.67	0.21		
medium	19.74	0.20		
small	15.92	0.14		
# manufacturers	26.99	0.32	10.59	0.10
big	13.18	0.10		
medium	25.14	0.29		
small	18.67	0.18		
# wholesale markets	28.95	0.35	12.46	0.14
big	16.56	0.15		
medium	26.91	0.31	13.27	0.15
small	26.00	0.30	10.02	0.09
# other type of commerce	19.18	0.19		
medium	16.72	0.15		
small	19.49	0.15		
# consulting for legal, business and investment	26.61	0.31	12.29	0.13
big	15.53	0.13		
medium	24.40	0.27		
small	24.57	0.28	12.61	0.14
# insurance companies	17.84	0.17		
medium	16.14	0.14		
small	14.73	0.12		
# unknown business	38.01	0.48	16.49	0.22
medium	29.45	0.35	14.34	0.17
small	37.96	0.48	15.80	0.20
# companies (big)	35.64	0.45	16.05	0.21
# companies (medium)	39.31	0.49	16.97	0.23
# companies (small)	35.64	0.45	14.90	0.18
# companies (total)	38.47	0.48	16.25	0.21
miscellaneous				
# cars (total)	16.27	0.14		
street length	26.69	0.31	13.39	0.15
purchasing power in retail per citizen	24.47	0.27		
purchasing power in retail in Mio €	33.84	0.28	10.87	0.11
purchasing power in retail (index)	24.66	0.28		

TABLE I. RESULTS OF THE OLS REGRESSION FOR BERLIN AND MUNICH. THE LISTED VARIABLES HAVE AN ABSOLUTE T-VALUE OF AT LEAST 10.

booking.
Variables that do not show a relatively strong influence are e.g. the age structure of a district or the number of children living in a household. As Schmöller et al. mentioned in [17] there is a slight impact which is however not peculiar regarding to other variables. This may has to do with a homogeneity in the population in both cities. There are no extremely poor, young or old districts within the operating areas so that the effect of these socio-demographic quantities is not evident.
Nonetheless, carsharing works good in areas with people who are receptive for new technologies, care about the environment and have the necessary money to afford this new mobility service.
A non-conservative attitude towards private cars is advantageous, too. In areas with a high percentage of people having a positive opinion on car leasing or a low car ownership rate carsharing works clearly better.

When including the five most robust, significant and informative variables stepwisely in a model, the following models are obtained.

Berlin		$adj.R^2$
+	number of services ($\approx$ 100 employees)	0.51
+	street length per district	0.58
-	distance to nearest long distance train station	0.64
+	rent index	0.67
+	number of households of the upper class	0.71

Munich		$adj.R^2$
+	number of administrations ($\approx$ 100 employees)	0.29
+	number of companies (>1000 employees)	0.33
-	distance to the airport	0.36
+	area size of the district	0.38
-	distance to nearest long distance train station	0.41

It is a bit confusing that companies with more than 1000 employees have a positive impact on the number of carsharing bookings in comparison with other variables in Munich. The authors assume that this variables counts all small and big offices of BMW that are distributed in almost every district of Northern Munich. BMW employees usually do not get a discount for the DriveNow fleet but tend to use the vehicles for trips from one office to another due to bad service by public transport in that part of the city. The airport of Munich far outside of the city is also an employer of more than thousands people and may effect this positive influence. The real influence is however the airport itself and not the size of the company.
So the variables are often not easy to interpret. Especially in Munich there are many factors like the parking prohibition for FFCS vehicles in the old city center or the ones mentioned above that bias the result.

2) Political tendency: The political trend in a district is taken from the results of the Bundestag election in October 2013. All in all there are 299 constituencies in Germany. These are again subdivided in polling districts each with one polling station. Almost 90 000 polling districts are distributed over the country. The number of citizens per polling district varies from a few hundreds up to 2500 in dense areas. They size is mainly based on the how good the residents can reach the polling

station which is in almost every case a school building.
To take absolute election results into account is hence not reasonable. And for a getting a transferable model for future times it is useful to neglect general political tendencies, too. The best way to get the political attitude of a district is thus to consider difference to the average election results in the city or to the constituency. By this, general nationwide appearing preferences for a party were filtered and the different election behavior of the polling districts becomes noticeable.
The election of the Bundestag contains two votes: The first is for the candidate of the constituency the second decides about the percentage of representatives of each party in the Bundestag. Whereas the first vote depends strongly on the sympathy for a particular candidate the second vote represents the best way the political tendency of the voter. Nevertheless, both votes shall be analyzed with the knowledge that the second vote is more informative.
Among others, the following parties stand for election:

- CDU/CSU: Christian Democratic (Social) Union that has a center-right political direction. The CDU stands for election in 15 of the 16 federal states; CSU is the counterpart in Bavaria (concerns Munich).
- SPD: Social Democratic Party of Germany: comparable with the Labor Party in the UK.
- Die Linke: A far-left party that was founded as the merger of the successor to the former Socialist Unity Party of Germany (SED) and the left-wing breakaway from the SPD.
- Bndnis 90/Die Grnen: The Greens evolves from the anti-nuclear power movement in the 1970s and concentrates nowadays primarily on the protection of the environment.
- FDP: The liberal party stands for liberalization in many parts of economy and society.
- NPD: A far-right party.
- Die Piraten: "The Pirates" arose a few years ago on the political horizon with the liberalization of the internet as a main goal and a basic democratically organized structure.
- AfD: The self-declared alternative for Germany is a new Eurosceptic party that political direction is clearly right-conservative.

The procedure of linear regression is the same as with the socio-demographic data. First, the results of all parties were taken in the model separately. The results are listed in Table II for Berlin and in Table III for Munich.

The results of the relevant parties are included in a linear model optimized by the method of ordinary least squares. When calculating the model with significant variables only, 50% (17%) of CS bookings in Berlin (Munich) can be explained by the political tendency of the people living in the district.
The models including all robust and significant variables shall not be listed in detail. The variables are not sorted and just the sign of the influence is mentioned.

	first vote		second vote	
	t-statistics	adj. R^2	t-statistics	adj. R^2
CDU	-4.12	0.02	-5.07	0.03
SPD	-6.04	0.05	1.00	0.00
FDP	5.52	0.04	6.95	0.06
DIE GRÜNEN	14.25	0.21	19.00	0.32
DIE LINKE	11.97	0.16	6.37	0.05
NPD	-10.84	0.13	-10.05	0.12
PIRATEN	-0.32	0.00	3.48	0.00
AFD	-11.04	0.13	-9.07	0.10

TABLE II. OLS REGRESSION FOR EVERY CONSIDERED PARTY IN BERLIN

	first vote		second vote	
	t-statistics	adj. R^2	t-statistics	adj. R^2
CSU	-0.77	0.00	-1.49	0.00
SPD	1.07	0.00	-1.02	0.00
FDP	4.21	0.04	4.03	0.04
DIE GRÜNEN	0.94	0.00	1.64	0.00
DIE LINKE	-2.22	0.01	-1.18	0.00
NPD	-1.81	0.01	-0.95	0.00
PIRATEN	3.24	0.03	2.03	0.01
AFD	-	-	-2.00	0.01

TABLE III. OLS REGRESSION FOR EVERY CONSIDERED PARTY IN MUNICH

Berlin		**Munich**	
+	CDU, 1.	+	SPD, 1.
-	SPD 1.	+	FDP, 1.
+	SPD, 2.	+	FDP, 2.
+	DIE LINKE, 1.	+	PIRATEN, 1.
+	DIE LINKE, 2.		
+	DIE GRÜNEN, 2.		
+	FDP, 2.		

It is remarkable to see that major parties may explain the booking demand when considering all robust variables whereas the single concern does not show a specific influence for every vote.
Small unconventional and innovative parties like the Greens and the Liberals are generally the most important positive factors in Berlin. Fig. 3 showing the ratio of votes for the conservative CDU and the Greens visualizes the correlation between polling districts with a high percentage of ecologic party voters and the near to the city center. In Munich, however, this category of variables failed as an explanation for CS bookings due to heterogeneity in the voting behavior.

3) Parking restrictions: The analysis of the influence of parking restrictions on the FFCS booking demand will not be done by a regression. The reason is that there are both a spatial and temporal component that has to be respected. An easy approach to see any tendency is to drawn the average number of bookings per hour and weekday for each of the 13 different parking zones. The graphs show strong differences towards each other that are caused by different frequency of some parking zones. It is hence necessary to standardized the number of bookings by the street length. The result of that evaluation is shown in Fig. 4.

Green lines and points represent bookings of the parking zone in time intervals in which parking was allowed, red colored ones are strictly speaking parking offenders. Usually the user gets a message on the onboard screen of the vehicle if the trips ends in a prohibited area. Since the restrictions vary over day time and the GPS signal may be imprecise

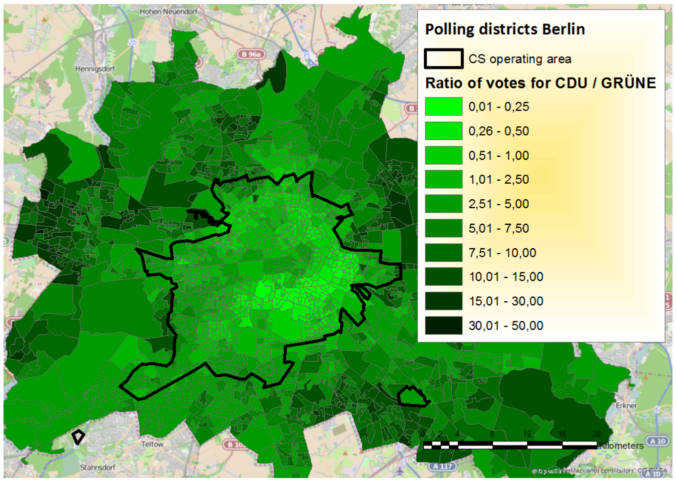

Fig. 3. Polling districts in Berlin colored by the ratio of the conservative party *CDU* and ecologic party *Die Grünen*

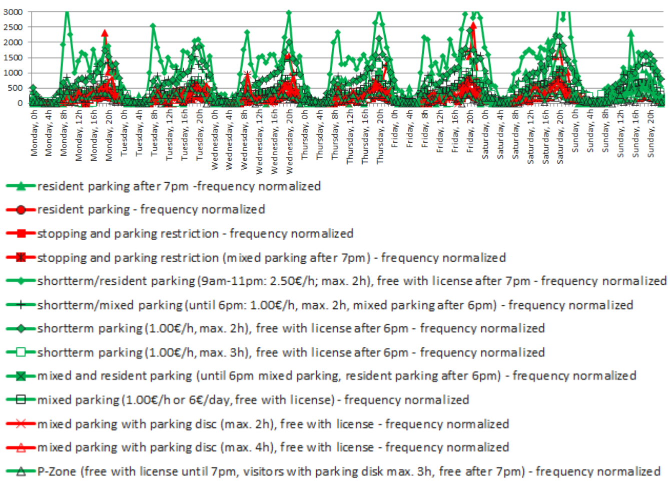

Fig. 4. Booking frequency for each parking zone in Munich

the operator rarely interdicts terminating the trip automatically. The message just advises the user to ensure that there is no parking restriction at that time and he has in case of non-compliance to pay a fine.
The evaluation shows that most customers follow the restrictions. But especially in the evening hours some users seem to be confused by the restriction or deliberately disregard the prohibition of parking for FFCS vehicles in some few zones. Another conspicuity is the typical morning and evening peaks that are clearly visible in every parking zone (see Fig. 5. Almost every zone seem to be homogeneously distributed. The exceptions are the shortterm parking zones. Especially on workdays the graph shows a much higher preference of customers for this kind of parking zone. The reason probably lie in the better availability of parking lots. In shortterm parking zones private cars are only allowed to park for a couple of hours and in the evening hours when shops close and the number of FFCS bookings increases these kind of parking lots are not blocked by private cars of the residents.

Although a preference for shortterm parking zones is evident it is hard to interpret this fact. One would go too far

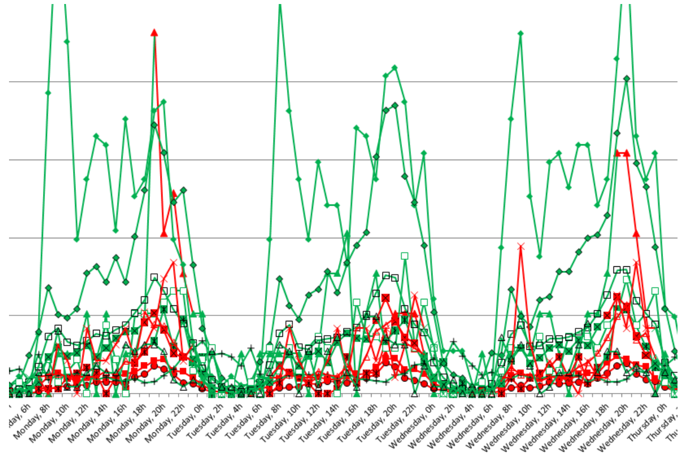

Fig. 5. Zoom of Fig. 4 to the first days

Temperature	Winter (Dec, Jan, Feb)	$< -2C$ ($< 28F$)
	Spring (Mar, Apr, May)	$< 5C$ ($< 41F$)
	Summer (Jun, Jul, Aug)	$< 15C$ ($< 59F$)
	Autumn (Sep, Oct, Nov)	$< 5C$ ($< 41F$)
Precipitation		$> 0.5mm$
Wind force		$> 3Bft.$

TABLE IV. DEFINITION OF BAD WEATHER CONDITIONS

when calling shortterm parking zones as an impact factor for FFCS bookings. It is better to say that restrictions for private cars promote the use of carsharing. This is a helpful point for municipalities: If FFCS shall be supported it is a good advice to reserve parking space for carsharing or reduce the attractiveness of existing parking lots for private cars.

4) Weather condition: The relevant data used to described bad weather are the temperature [in C], precipitation [in mm] and the wind force [in Bft.]. One option would be to take these data and find an antiproportional or proportional relationship between the number of bookings and the three variables. But it is assumed that the weather in general is more important for the choice of transport mode than the quantity of rain or the like. Therefore it is more useful to find a tolerance limit from the combination of the three variables. An exceeding of this limit means that most people estimate the weather as "bad" and are probably more willing to choose a car for their way.
A bad weather day is in that work considered as a day with a lower mean temperature than the previous day and a precipitation during the day in addition. Good weather days are on the contrary days with a higher mean temperature than the previous day with no precipitation over the day at all. One problem of this definition is that there are days, e.g. those with precipitation and a higher mean temperature, that cannot be assigned to this characteristic. Further, the classification does not help for the current case since it is too imprecise.
As a solution, the official formulations for weather news published by the DWD (see [23]) were used to find an appropriate definition of bad weather conditions.

In Table IV the conditions of bad weather are listed. At least one of the linked conditions has to be fulfilled to speak of bad weather. In the lexicon of the DWD (see [22]) the Beaufort scale is explained. A wind force of 4 and more

daytime	T	*df*	p-value	daytime	T	*df*	p-value
6am	1.189	9	0.265	3pm	1.100	8	0.303
7am	-0,777	9	0.457	4pm	1.054	9	0.319
8am	0.917	10	0.381	5pm	-0.929	8	0.380
9am	0.602	9	0.562	6pm	2.312	8	*0.050*
10am	1.449	9	0.181	7pm	2.148	9	*0.060*
11am	-1.382	8	0.204	8pm	1.135	7	0.294
12pm	0.895	7	0.400	9pm	0.555	8	0.594
1pm	1.384	9	0.200	10pm	1.053	9	0.320
2pm	0.623	7	0.553	11pm	0.557	9	0.591

TABLE V. RESULTS OF THE PAIRED T-TEST FOR THE HEAVY USER DATA SET 1 (BERLIN), CITED FROM [14]

daytime	T	*df*	p-value	daytime	T	*df*	p-value
12am	4.651	6	*0.003*	12pm	-0.790	6	0.459
1am	0.511	6	0.628	1pm	0.347	6	0.740
2am	0.317	6	0.762	2pm	-0.516	6	0.624
3am	-1.205	6	0.274	3pm	-1.167	6	0.287
4am	0.583	6	0.581	4pm	0.932	6	0.387
5am	-0.041	6	0.968	5pm	0.978	6	0.366
6am	-0.505	6	0.632	6pm	1.329	6	0.232
7am	-0.246	6	0.814	7pm	-0.486	6	0.644
8am	1.190	6	0.279	8pm	-1.600	6	0.161
9am	-0.820	6	0.443	9pm	-2.052	6	*0.086*
10am	-0.047	6	0.964	10pm	-1.341	6	0.229
11am	0.516	6	0.624	11pm	0.203	6	0.846

TABLE VI. RESULTS OF THE PAIRED T-TEST FOR DATA SET 2 (BERLIN)

means a wind with more than 15 km/h. Riding a bicycle as an alternative transportation mode is then definitely not comfortable.
Both data sets are regarded: The heavy user data set for Berlin from 2012 and the one containing all bookings of Berlin and Munich from 2013.
Every hour of the analyzed booking period is checked if there were bad or good weather conditions. By this, two distribution of booking frequencies were calculated. Since also the day time is supposed to have an influence the two distributions were compared hour by hour.
The paired t-test testing if the mean of the good and bad weather sample is significantly different is applied for two data sets. The test for the first data set in Berlin shows that there are significantly more bookings between 6pm and 8pm on days with bad weather condition at that time (see Table V). In the second test, however, no distinct significance is observable for Berlin (see Table V). In Munich, the test shows significantly more bookings during bad weather conditions in night hours. But it must be interpreted more carefully. Due to the reason that the general level of booking frequency is lower during the night the difference in the mean of the bad and good weather distribution appears more easier. The significance should thus not be emphasized to much.

In consequence, the authors assume that uncomfortable weather conditions generally do not change the entire booking frequency but users who are familiar with the FFCS system are inclined to take a car when it is raining. Schmöller et al. considered in [17] the change of weather conditions during a day and discovered that there are more bookings when the weather turns bad during the day.

daytime	T	*df*	p-value	daytime	T	*df*	p-value
12am	4.569	6	*0.004*	12pm	0.386	6	0.713
1am	2.177	6	*0.072*	1pm	0.986	6	0.362
2am	2.526	6	*0.045*	2pm	0.367	6	0.726
3am	2.379	6	*0.055*	3pm	0.575	6	0.586
4am	5.468	6	*0.002*	4pm	0.081	6	0.938
5am	3.622	6	*0.011*	5pm	-0.652	6	0.538
6am	3.154	6	*0.020*	6pm	1.868	6	0.111
7am	-2.328	6	*0.059*	7pm	-0.733	6	0.491
8am	-0.548	6	0.604	8pm	0.458	6	0.663
9am	-1.329	6	0.232	9pm	0.036	6	0.972
10am	-0.635	6	0.549	10pm	3.382	6	*0.015*
11am	0.971	6	0.369	11pm	3.405	6	*0.014*

TABLE VII. RESULTS OF THE PAIRED T-TEST FOR DATA SET 2 (MUNICH)

B. Conclusion

Summarizing, the entire work demonstrates the difficulty of finding a clear explanation for the success of CS in particular districts. Nevertheless, some indicators can be identified. Centrality as well as the density of services play an important role for the FFCS demand. It is clear that FFCS is usually not used for recurrent trips in cause of the high price of the system. To provide an interesting offer for the customer the carsharing operator has to ensure that spots with a high attractiveness for leisure time activities are included in his operating area.
A high density of places for spending one's leisure time correlates with an increase of CS bookings. A short distance to the city center has a positive impact comparable to that of districts with a high percentage of citizens with an open-minded political attitude.

Taking the different parking restriction zones into consideration there is no preference noticeable with the exception of shorttime parking zones. The advantage of parking availabilities in these spots is the high fluctuation of vehicles. There are no private cars of residents over the day and all other avoid the comparatively high fees per hour. These kind of parking restriction can be taken as option of the municipality to offer FFCS vehicles a good parking facility and promote this mobility system.

The weather seem to play a role for heavy users only. They tend to use FFCS vehicles more often during bad weather conditions in the early evening. It is probable that this fact has to do with the purpose of the trip: Are ways during the day mostly routine trips and done with the same kind of transport mode the trips in the evening are mainly non-recurrent and for leisure time activities. Then a person who is familiar with the FFCS system is more willing to use a vehicle if the weather conditions are not brilliant. Moreover, it is worth to think about another test design. Future research may not distinguish between two weather conditions but categorize the weather. Eugster proposes in the end of his study (see [5]) to consider variables like air pressure and cloud cover additionally to describe the subjective feeling of the current weather development in a better way.

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