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Empirical analysis of free-floating carsharing usage: The Munich and Berlin case

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A B S T R A C T

Carsharing has become an important addition to existing mobility services over the last years. Today, several different systems are operating in many big cities. For an efficient and economic operation of any carsharing system, the identification of customer demand is essential. This demand is investigated within the presented research by analyzing booking data of a German free-floating carsharing system.

The objectives of this paper are to describe carsharing usage and to identify factors that have an influence on the demand for carsharing. Therefore, the booking data are analyzed for temporal aspects, showing recurring patterns of varying lengths. The spatial distribution of bookings is investigated using a geographic information system and indicates a relationship between city structure and areas with high demand for carsharing. The temporal and spatial facets are then combined by applying a cluster analysis to identify groups of days with similar spatial booking patterns and show asymmetries in the spatiotemporal distribution of vehicle supply and demand.

Influences on demand can be either short-term or long-term. The paper shows that changes in the weather conditions are a short-term influence as users of free-floating carsharing react to those. Furthermore, the application of a linear regression analysis reveals that socio-demographic data are suitable for making long-term demand predictions since booking numbers show quite a strong correlation with socio-demography, even in a simple model.

1. Introduction

For decades, the privately owned car carried very high importance as a status symbol. Moreover, it was promoted as the most important mode of transportation by many city planners and an adequate infrastructure was provided for it. Rethinking this viewpoint is a global trend today. Especially for young adults, owning a private car seems to be less important when compared to the past whereas modern technologies like mobile phones gain a higher importance (Zipcar, 2014). The assumption of private car ownership losing importance is also supported by the fact that car use – measured in vehicle miles traveled per capita – is decreasing (Davis et al., 2012; Kuhnimhof et al., 2012) and the percentage of persons holding a driver's license (Davis et al., 2012; Delbosc and Currie, 2013) has also dropped in many industrialized countries. In the past years, researchers identified several factors that could possibly explain this development (e.g. affordability or attitudes

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towards the car). Yet for most of these factors, it is still unclear how strong an influence they have (see (Delbosc and Currie, 2013) and references within for a summary).

Despite this development, many large cities have to deal with traffic problems today. These are mainly caused by continued urbanization (United Nations, 2014) and the corresponding population growth in cities. Since the negative impacts of vehicular traffic – such as noise or air pollution – are widely known today, policymakers address this topic with increasing sensitivity. The public sector in particular considers measures for counteracting environmental pollution and traffic in cities. Possible measures already in place are usually aimed at existing modes of transportation, and include the implementation of congestion charging (which has already proven to have positive effects in the charged areas (Beevers and Carslaw, 2005)), promoting public transport, or enhancing bicycle infrastructure.

However, some rethinking also takes place in the private sector. Sometimes this is driven by environmental awareness or idealism but sometimes also by seeing an opportunity to turn a profit out of a global trend. Either way more and more environmentally-friendly concepts are being offered now. One part of this trend is offering new mobility services which should be viewed as supplements to existing ones. Carsharing is one of these new services: it is becoming an integral part of the cityscape in many big cities today. In carsharing systems, vehicles are provided to registered customers for short-term rentals. Becoming a member of the carsharing organization is a mandatory step in order to get access to the cars and can usually be done by everyone with a valid driver's license. Fees to be paid are generally calculated per kilometer traveled, by duration, or a combination of both and cover both fuel and insurance. One indicator pointing to the importance of carsharing is the growth in membership numbers; this currently exceeds 10% per year in both North America and Germany (Shaheen and Cohen, 2014; Bundesverband CarSharing, 2014). At present, one can distinguish three main types of carsharing: station-based (with two subtypes), free-floating (which will be the focus of this paper) and peer-to-peer carsharing.

In a station-based system, the operator specifies positions for stations (usually parking spots reserved exclusively for this purpose) and parcels out vehicles among these stations. Depending on the operator, there are two different forms of station-based carsharing: in the first (operated e.g. by Zipcar in the US or Flinkster in Germany), only round trips are allowed, meaning that a trip has to end at the same station where it started. In the second form (run e.g. by Autolib' in Paris, France or tested by Zipcar in Boston, MA), mostly called one-way carsharing, cars can be returned to any of the designated stations, independent from where the trip started. This possibility increases flexibility for users but it also creates new problems for the operator. Since a return trip is not always made, it is very likely that at times there is a spatial imbalance over the stations. The operator still has to ensure that there are enough cars and enough parking spots at every station to cover demand most of the time. Consequently, there may be the necessity to relocate cars from one (overfilled) station to another (mostly unoccupied) station. However, any relocation causes an additional trip which results in additional costs for the operator and further pollution of the environment. The implementation of a "good" relocation method therefore is an important task and thus addressed by many researchers (Nair et al., 2011; Di Febbraro et al., 2012; Jorge et al., 2014). Other studies primarily concentrate on the customers and their use of carsharing as this knowledge could help spread carsharing further. Different surveys from around the world (see (Millard-Ball et al., 2005) and references within) show that most users of station-based carsharing are between 25 and 45 years old, live in a rather small household (one or two persons) and have an income and educational level above average. Studying the usage of station-based carsharing shows that the highest number of rentals occur on Fridays and Saturdays (Concas et al., 2013) and most trips are made for shopping, social-recreational purposes or personal business (Cervero, 2003; Cervero and Tsai, 2004; Cervero et al., 2007). When trying to increase the acceptance of carsharing one last point is very important to mention: one study shows that station-based carsharing reduces greenhouse gas emissions (Martin and Shaheen, 2011).

The type of system that will be the focus of this paper is free-floating carsharing (operated e.g. by DriveNow or car2go). Such a system often is operated by car manufacturers and also allows for one-way trips, but does not make use of stations. Instead, an operating area is defined and contracts with the municipalities ensure that cars can be parked at almost any free parking spot within this area. Assuming that each single station only attracts customers within a certain distance to the station (comparable to maximum acceptable walking distances to transit stations (O'Sullivan and Morrall, 1996)), using an operating area may attract more people because cars can be used even in areas where a station would not be profitable. The first systems of this type were implemented only few years ago; consequently, there is hardly any literature about free-floating carsharing. As with station-based carsharing, one study claims free-floating carsharing to have positive environmental effects because it reduces CO_2-emissions (Firnkorn and Müller, 2011). This result must be viewed with some criticism however, because of its very simplistic approach and, among others, the usage of total membership numbers (which are described as an unreliable variable later in the presented paper). Further studies attempt to describe the impact of carsharing on other modes (Firnkorn, 2012). To the authors' knowledge, only one study dealt with actual free-floating carsharing usage and the socio-demography of users (Kortum, 2012). Free-floating carsharing could also be referred to as a special case of one-way carsharing. Once again, this shows that there is a need to address the relocation problem, but the authors can infer from the lack of stations that there is an additional necessity for knowing exactly where cars are most likely to be rented again (Weikl and Bogenberger, 2012). Looking into the future, shared autonomous vehicles could be treated as a possible special case of free-floating carsharing. Those are assumed to have a great positive impact on the environment, even if the total amount of vehicle-miles traveled is expected to rise (Fagnant and Kockelman, 2014).

Another development on the market is peer-to-peer carsharing, in which private persons provide their own cars for renting. This way, private cars (most of which are unused 90% of the time (Shoup, 2005)) receive a higher average utilization and car owners are helped reducing the costs for maintaining their own cars. Operators of such a system usually do not offer own cars. Their main task is to provide insurance and pair up car owners with renters. The systems are mostly characterized by a higher flexibility in pricing since car owners themselves can – to a certain extent – define the fee for renting their car. The operator (e.g. RelayRides in the US or Autonetzer in Germany) covers expenses by receiving a certain proportion of the total rental fee. As this form of carsharing also is quite new on the market, literature is also very limited. Up to now, most studies concentrate on the (potential) market, the users' demography or their motives for joining the system (Hampshire and Gaites, 2011; Ballús-Armet et al., 2014; Clark et al., 2014; Dill et al., 2014).

As mentioned before, this paper deals with the free-floating carsharing system of one German operator and how it is used in the two cities of Munich and Berlin. In the period of investigation, this operator supplied a total of approximately 300 vehicles in Munich and 600 vehicles in Berlin; these numbers varied slightly within the time period in consideration. In total, six different car types were available, classified into the segments B, C and J, using the classification scheme from the European Commission (Commission of the European Communities, 1999). All of these vehicle types are primarily intended for transporting people. Suitability for transporting large goods is limited. The different car types are also factored into the operator's charging system. Rental fee is exclusively determined by the duration of the booking (approximately 30 ct/min) but slightly higher for larger cars. There is also the possibility of buying package deals – i.e. customers can buy time credits at reduced rates – but unused credits expire after a predetermined period. As there may sometimes be the necessity of making a round-trip with several stops, the possibility to park and leave the car without ending the rental is given. This is charged with about half the price per minute. A booking can be made in two different ways. The first way is searching and reserving available cars over the internet or a mobile app. Reserving can be done at no cost. However, if the actual trip does not start within fifteen minutes, the reservation expires and the car is made available for all customers again. The second way is spontaneously renting an available car parked on the street. For this purpose, all of the cars are equipped with a display in the front window; this shows the cars' availability status.

The purpose of this paper is to describe how customers of free-floating carsharing actually use the service. Therefore, both temporal and spatial distribution of rentals is described. It is shown that the highest percentage of bookings takes place on Saturdays and that the temporal distribution over the course of a day varies greatly between workdays and weekends. Furthermore, it is shown that the spatial distribution of bookings changes over time and that, at least to a small extent, it can be described by the socio-demography of the different areas of a city. In the first part of this paper, the available data and the methods used to evaluate these data are described. Afterwards the results describing the actual usage by means of temporal and spatial aspects are presented as well as potential external influences on usage. In the final section, some conclusions are drawn and an outlook on future research is given.

2. Methodology

For the purpose of describing actual usage, several data sets are used. Two of them were provided directly by the carsharing operator as part of a research project; the others were obtained from external sources.

The first data set obtained by the operator contains the current number of vehicles and registered members for both cities for each day of the investigation period. In contrast to other researchers who utilize this variable (e.g. (Firnkorn and Müller, 2011)), the authors of the presented paper consider the usage of membership numbers problematic for several reasons. First, not every registered member uses carsharing regularly. Since there is no monthly base fee, there is no need to cancel membership. This means there are people registered who are not using the service anymore. Second, the operator occasionally runs special promotions to acquire new customers by foregoing registration fees. This means there may also be registered customers who have never used this service at all but seized the opportunity to get a free membership just in case they want to use it sometime. For these reasons, the authors have decided not to use membership numbers for their analyses. Nevertheless, it is important to know that membership numbers are growing steadily and the operator therefore has a good reason to extend the operating area to accommodate even more potential customers. Such growth occurred several times within the investigation period. Since these changes could affect the spatial analyses, for the purposes of this study, the operating areas of both cities investigated have been limited to the areas they covered at the beginning of the investigation period, as depicted in Fig. 1. The red dashed polygon in Munich marks the so-called "Altstadtring", the boundary of the city center, where it is not allowed to park carsharing vehicles.

The second and most important data set contains the booking data of the operator for a period of two years, from November 1, 2011 to October 31, 2013. Whenever a vehicle of the fleet is rented, an entry is made into the database on the operator's backend server. Every entry in this dataset contains the most important information about the corresponding trip. The variables that are recorded can be seen in Table 1, differentiated between the ones recorded at trip start and trip end. As the operator has to conduct service trips from time to time (e.g. for refueling, cleaning or relocating the cars), the variable "trip type" differentiates the two types "service" and "customer". The total duration of a trip is split into the two variables "time in driving mode" and "time in parking mode", because of the differentiation in the pricing model mentioned in Section 1.

This entire database was made available for the presented investigations. To this purpose, it was exported into Excel spreadsheets, with one file for every month and city. Because of the large size of the given data, it was important to find software that enabled the authors to answer any questions that arose. First attempts to work directly in Excel failed due to the high number of entries. The software MATLAB was then found to be well suited for the intended calculations.

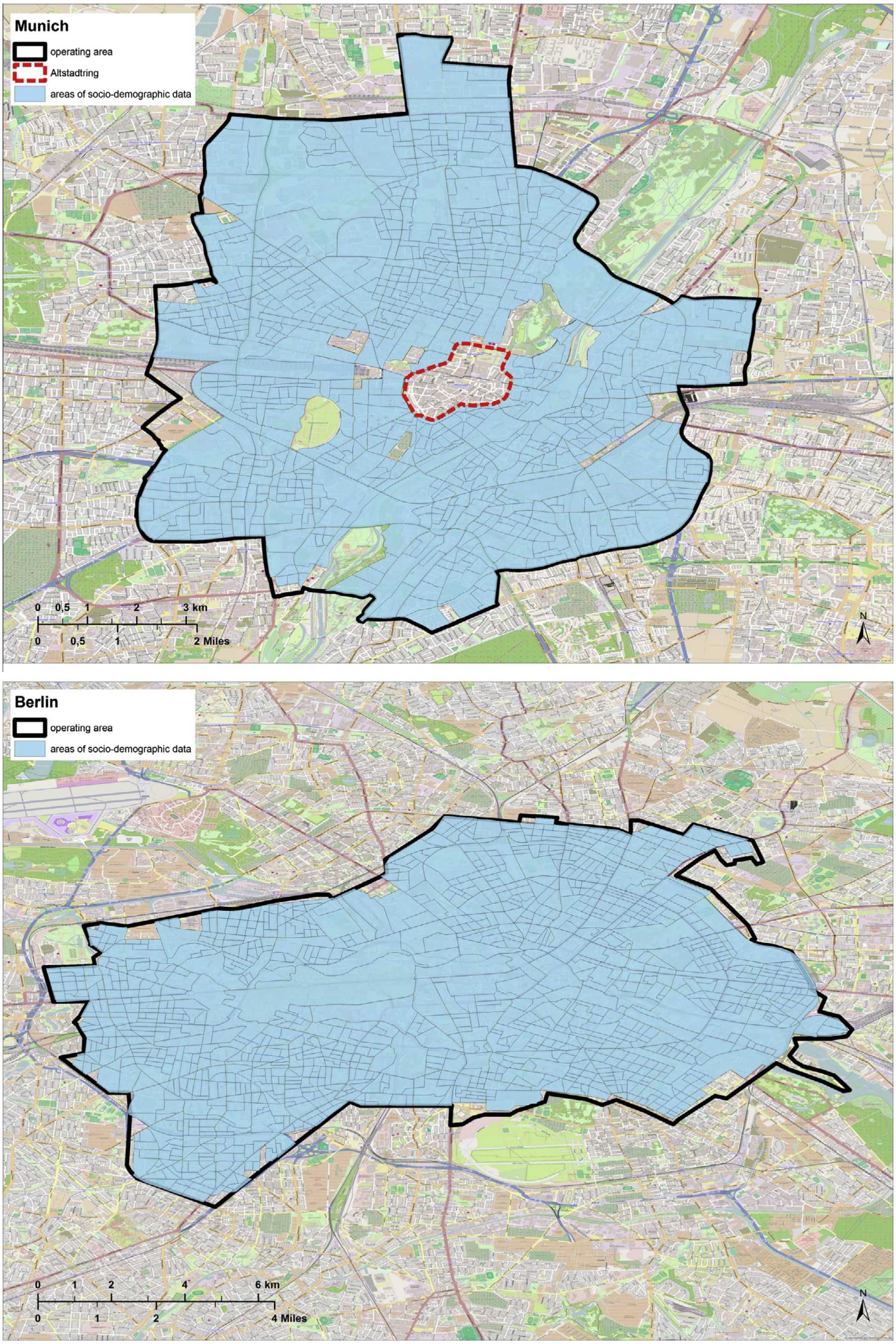


Fig. 1. Operating areas and areas with socio-demographic data available for Munich (top) and Berlin (bottom).

Table 1
Variables that are recorded when a booking is performed.

Trip attributes recorded at trip start	Trip attributes recorded at trip end
Timestamp (in the form *dd.mm.yyyy HH:MM:SS*)	Timestamp
GPS-coordinates of current location	GPS-coordinates of current location
Unique vehicle ID	Distance covered
Unique customer ID	Time in driving mode
Trip type	Time in parking mode

For this purpose, a script performing all steps is created, starting with loading the data and finishing with an output containing all results of the analyses. The first step after loading the data is to preprocess the data set. This step is necessary because the manner in which data are exported from the backend server they also contain unwanted and faulty entries. The unwanted entries are easy to identify: keeping in view the objective of describing the customers' usage, all service trips included in the data have to be deleted. Faulty entries may have their origins in several reasons. These include the absence of GPS-signal, failure to transmit information to the server or (at least once) a server breakdown. These problems may cause a variety of faulty records – identifiable e.g. by missing coordinates, unrealistically high average speed values or a deviation between stated and computed duration – which have to be deleted because they are unreliable. A further part of preprocessing includes the computation of additional fields that are needed for the analyses like Euclidean distances between start and end of the trips. Since MATLAB works vector-oriented, all entries can be processed at once and so all of the operations are performed in a reasonable amount of time. The same applies to the next part of the script, in which the remaining data are evaluated for different aspects and several output graphs are created.

With the given booking data, it is also possible to identify imbalances between supply and demand. In order to find such imbalances, the first year of the booking data in Munich are used to conduct a spatiotemporal cluster analysis with MATLAB. For this purpose, each of the 366 days analyzed is divided into seven time slices. The first is a 6-h time slice, from midnight to 6 a.m. The remaining time slices cover the rest of the day with periods of three hours each. For macroscopic modeling purposes, the operating area is divided into 10 areas, as seen on the left of Fig. 2. Afterwards, the number of bookings in each area is counted for each time slice for each day so that in total 366 vectors with 10 entries each are obtained for each time interval, as illustrated on the right of Fig. 2.

In the next step, for each time interval, those ten-dimensional vectors containing the booking frequencies are reduced into two dimensions by applying a principal component analysis in MATLAB. The resulting two-dimensional points can then be visualized with the (unidentified) principal components as axes. Afterwards, the points can be grouped into clusters by applying the *k*-means cluster method in MATLAB. Throughout the analysis of all time slices, six turns out to be the most appropriate number of clusters to represent the distribution of the points. So, for all time slices, the number of clusters to use for this method is predefined as six. The *k*-means cluster method partitions the points into clusters by executing the following steps: first, randomly chosen points taken from the total set are defined as cluster centroids (in the presented case, six points), then each of the remaining two-dimensional points is assigned to the cluster where its distance to the cluster centroid is minimal. Finally, these distances are summed up for all points within the different clusters. Afterwards, an iterative process is started. New centroids are computed as the center of all points within the corresponding cluster in every iteration. All points are then assigned to clusters again using the new centroids. As illustrated in an exemplary fashion in Fig. 3, these steps are iterated until the centroids no longer change. The example also shows one drawback of the chosen method. A seemingly unique partition into clusters may not be found if the initialization is made in a "bad" way. In order to fix this problem, the method tries several initializations and chooses the best clustering.

In order to obtain a more precise view over the actual usage, it is necessary to look at the spatial distribution of the starting and ending points of the trips. This is done by computing Hot Spots using the geographic information system ArcGIS. In

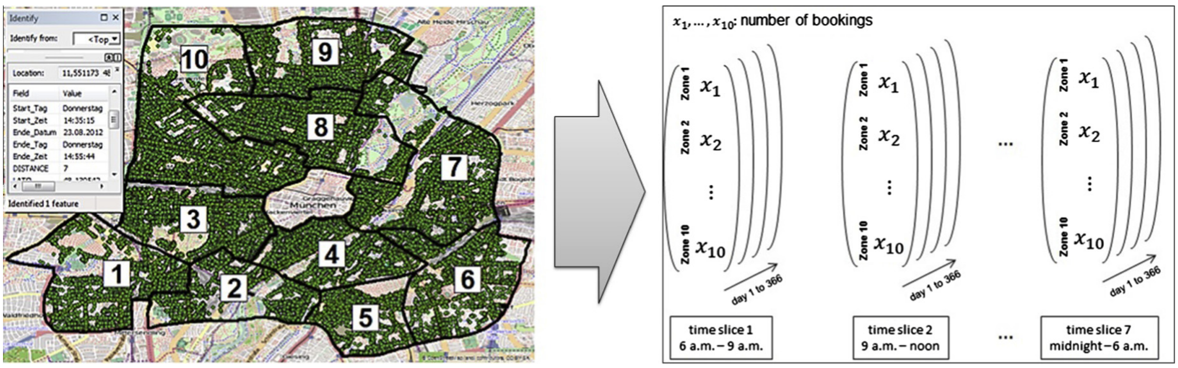


Fig. 2. Booking data of all ten areas are combined in one vector for each day and time slice.

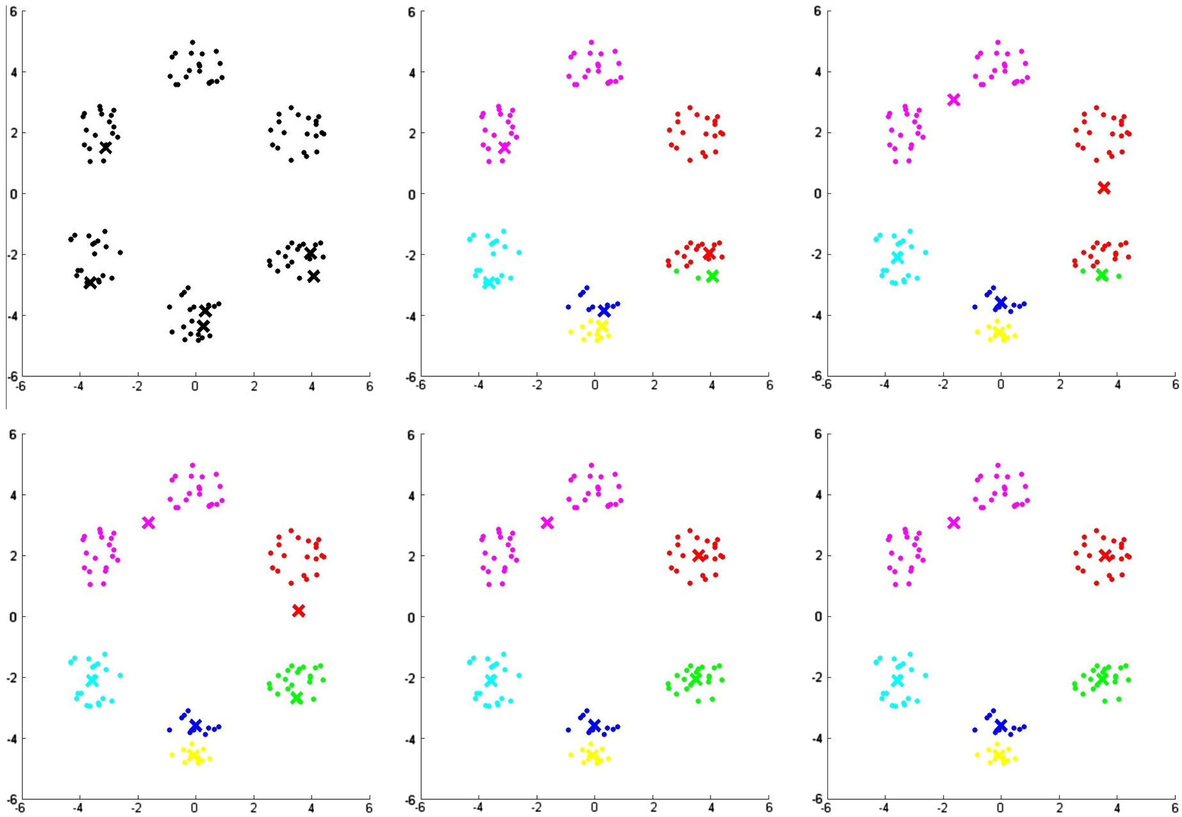


Fig. 3. Example for the *k*-means cluster method.

the context of this paper, a Hot Spot is an area where – when compared to the average – a statistically significant higher number of bookings occurred. The first step in computing these Hot Spots is to superimpose a grid over each operating area. In the presented case, this grid consists of square cells with an edge length of 100 m each. Next, for each cell of the grid, the number of trips which started or ended within the cell is counted. For computing the corresponding Hot Spots, a predefined ArcGIS toolbox is used. This toolbox performs the Getis-Ord Gi*-test (Getis and Ord, 1992; Ord and Getis, 1995) that computes a *z*-score for each cell by considering all cells within a (predefined) search radius. Depending on the settings, cells with a greater distance can be weighed differently so the formula used for calculating the *z*-scores of cell i is defined as follows (Esri, ArcGis Resources, 2015):

$$G_i^* = \sqrt{n-1} \cdot \frac{n \cdot \sum_{j=1}^{n}(x_j \cdot w_{i,j}) - \left(\sum_{j=1}^{n} x_j\right) \cdot \left(\sum_{j=1}^{n} w_{i,j}\right)}{\sqrt{n \cdot \sum_{j=1}^{n} x_j^2 - \left(\sum_{j=1}^{n} x_j\right)^2} \cdot \sqrt{n \cdot \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2}}$$

$n =$ total number of cells

$w_{i,j} =$ weight of cell j with respect to cell i

$x_j =$ number of bookings in cell j

In the presented case, only the up to four direct neighbors sharing an edge with the considered cell are regarded and are all weighed equally with 1. The complete procedure is depicted schematically in Fig. 4. In the last step, the cells are colored depending on their *z*-score so that Hot Spots (cells with a high *z*-score) and Cold Spots (cells with a low *z*-score) can be identified easily.

To the knowledge of the authors, so far there is no literature about the socio-demography of free-floating carsharing customers. Unfortunately, the booking data does not contain any personal information that could be used to close this gap. But

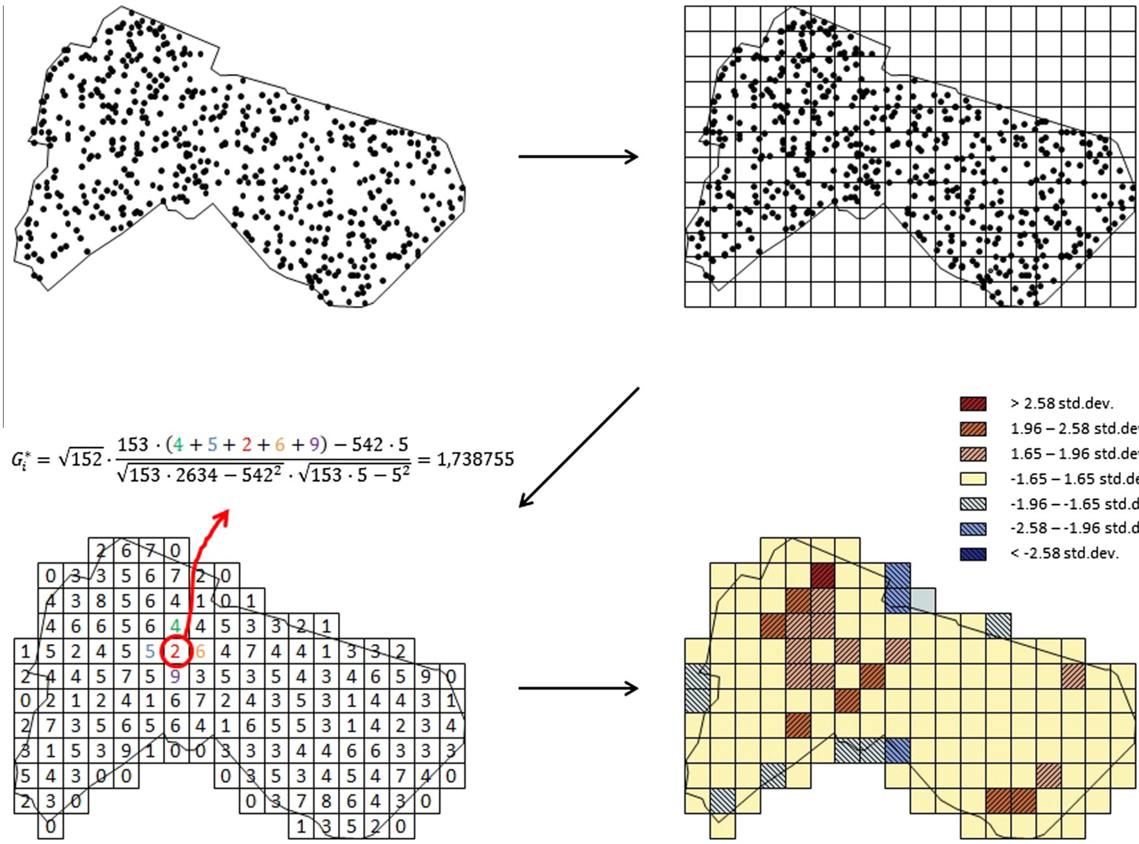


Fig. 4. Example for the procedure of computing Hot Spots.

with knowledge about where trips started, it is possible to gather some clues about who the customers are. For this purpose, a third data set containing information on the socio-demography of both cities is obtained by infas, an institute for social research and market research (Infas Institut für angewandte Sozialwissenschaft GmbH, 2015). These data divide each city and its metropolitan area into smaller areas averaging 0.075 km^2. For each of these small areas, the database contains information about social and demographic aspects such as age structure or income distribution within the area. The procedure for describing a correlation between booking numbers and socio-demography is again performed with ArcGIS and it is similar to the one for computing Hot Spots: as a first step, all areas which do not overlap with the operating area are eliminated. Next, all areas with a population of less than 50 are also excluded from the analysis for two reasons: First, mainly industrial areas should not influence the investigation and second, a small population is more likely to generate an atypical socio-demographic distribution since outliers have a higher influence. After this step, 762 areas in Munich and 1153 areas in Berlin remain for being considered in the analysis; these areas can be seen in Fig. 1. After the number of areas is reduced, the next step is counting the number of bookings in each area and dividing it by the size of the area. This provides comparability between the areas since their size no longer has an influence on the result. In the last step, this normalized number of bookings is used as dependent variable in linear regression models with singular explanatory variables. For each of the given socio-demographic variables one model is calculated using the data as values of the explanatory variable. This way, for each of the given variables, it can be determined whether it has a positive or negative effect on the booking frequency. Also, the coefficient of determination can be calculated for each variable without having to take care of multicollinearities.

3. Empirical results

With the given data, each of the following analyses could be conducted by examining the time and place of either the start or end of each trip. In order to keep the length of the paper in a reasonable extent, as a convention only trip starts are considered in the following. When looking for temporal patterns this convention is acceptable. The average duration of a booking is less than one hour so it is to expect that the results would show only small differences when using end times instead. When looking at spatial patterns, however, it is more critical. In case the entire set of bookings is considered, the convention is still acceptable, as each customer trip starts where another ended – as long as no service trip was conducted in the meantime. But when looking at shorter time intervals it is very likely that areas with frequent trip starts and areas with frequent trip ends are located in different parts of the city. For this reason the limitation on trip starts has to be seen as a strong restriction in such cases.

3.1. Temporal analyses

With the growth in membership numbers mentioned in Section 1 it is to expect that the number of bookings is also growing with time. Therefore, in a first step, the number of bookings is calculated for every single day of the investigation period. The maximum number of bookings occurring on any day is defined as 1 and all other values are scaled respectively in order to conceal the real absolute values. The result of this calculation is shown at the top of Fig. 5 and some interesting facts can be derived.

Some of these facts are easily explained: at the beginning of the investigation period, there are fewer bookings in Berlin because operations just started one month prior, whereas in Munich it had already been operational for almost five months. Another noticeable point encompasses a server breakdown in Berlin at the end of October 2012 during which no rentals were recorded at all. Finally, there is a drop in the number of bookings on the days around Christmas with a single peak on New

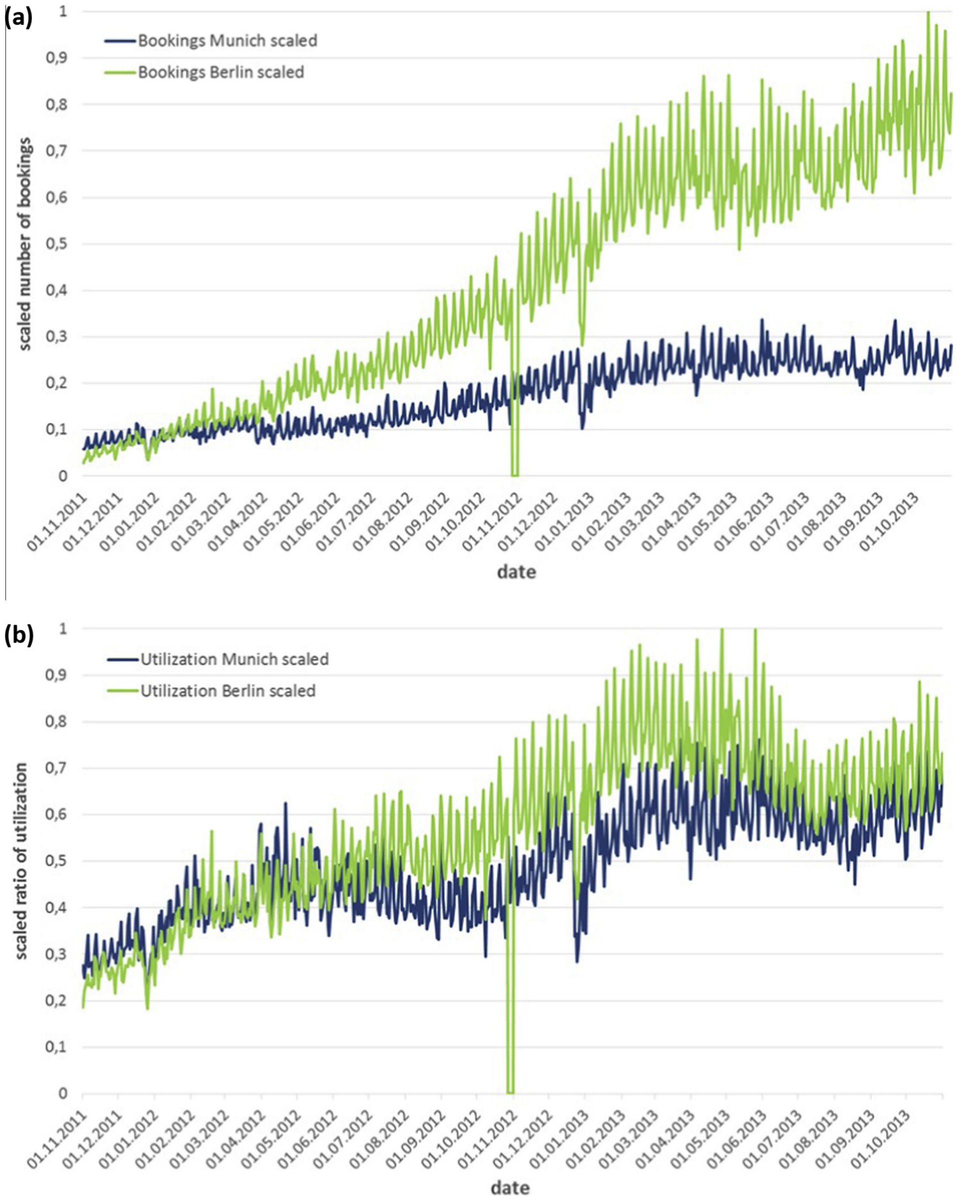


Fig. 5. Development of bookings (top) and car utilization (bottom) on a daily basis.

Year's Eve. Other findings can only be explained by also looking into the first dataset containing vehicle and membership numbers. It can be seen that booking frequency stagnates in Munich at the end of the investigation period whereas it steadily grows in Berlin all the time. With the number of registered members steadily growing in both cities and without knowledge about the number of active (however this may be defined) members, this cannot be an explanation for the observed development. On the other hand, the diverse developments may be explained by the number of vehicles available. This number is also increasing in Berlin over the whole period whereas in Munich it is almost constant all the time. So in order to find a connection between the number of bookings and number of available cars, a second graph is shown in Fig. 5. In this chart the number of bookings on each day is divided by the current total size of the fleet in the corresponding city. Again the numbers are scaled by the maximum value. In this graph it can be seen that the average utilization of a car is slightly higher in Berlin compared to Munich. Another point that may be worth observing in the future is a decline in the average utilization in both cities over the months from June to September. One possible explanation for this effect could be that, during the summer period, users of free-floating carsharing use other modes such as walking or cycling.

All curves in Fig. 5 also show similar fluctuations with peaks that seem to occur in regular intervals. Looking at the exact dates of these peaks shows that in most cases there is an interval of one week between two occurrences. This behavior suggests that there are days of the week where carsharing demand is higher compared to the other days. In order to confirm this assumption, each booking of the investigation period is assigned to the day of the week when it started. The total number of bookings is then counted for the different days of the week as displayed in Fig. 6.

This figure shows that on the days from Monday to Thursday, the booking numbers increase slightly but stay on a comparable level between 13% and slightly more than 14%. In contrast, the number of bookings is considerably higher on Fridays with approximately 16% and especially on Saturdays when nearly 17% of all bookings take place. On Sundays, the number of bookings declines and is on one level with Monday to Thursday. Comparing this distribution with one of station-based carsharing (Concas et al., 2013), some differences can be observed: free-floating carsharing is used more often at weekends (with a total of approximately 30% of all bookings taking place at weekends compared to approximately 27%) but station-based carsharing has a considerably higher booking frequency on Fridays (approximately 19% compared to approximately 16% in free-floating carsharing).

In order to gain an even deeper insight into the customer usage of free-floating carsharing daily curves are created. This is done by using 24 one-hour intervals (from midnight to 1 a.m., from 1 a.m. to 2 a.m., and so on) and counting the number of bookings that started in the different time intervals. As trip purposes are assumed to differ between workdays and weekends, the bookings are further differentiated in Fig. 7. Since only approximately 30% of all bookings taking place at weekends, the graphs are weighed by the total number of trips on workdays or weekends respectively. In order to compare the distribution of carsharing rentals with private car use, two more curves are added in Fig. 7. These show the trip distribution of private cars on workdays and weekends as they are obtained using the data of the MiD, a representative German survey (Bundesministerium für Verkehr und digitale Infrastruktur, 2008), and including only cities with at least 500,000 inhabitants (such as both Munich and Berlin).

The first aspect that draws attention is the carsharing curves for Munich and Berlin being nearly identical. This is an interesting fact as the curves differ strongly from the one describing private car use. Both carsharing curves for workdays show one peak between 8 a.m. and 10 a.m. and a second, even higher peak between 5 p.m. and 8 p.m. Both of these peaks occur later than the ones of workday trips with private cars. In contrast, at weekends, there is no such distinct peak in carsharing usage. The majority of weekend trips start later when compared to workdays and are spread out over the whole day, with only one slight peak between 7 p.m. and 8 p.m. Nighttime trip ratios are also of note. The ratio of carsharing trips starting

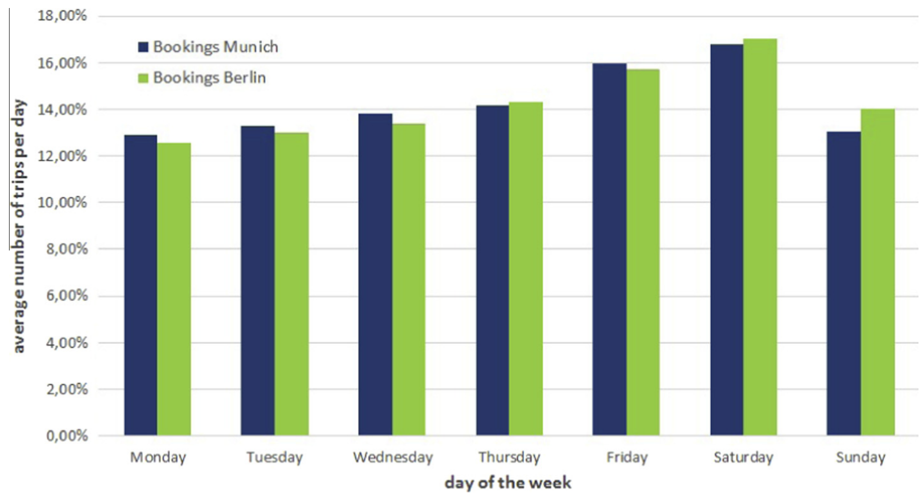


Fig. 6. Average number of bookings on the weekdays.

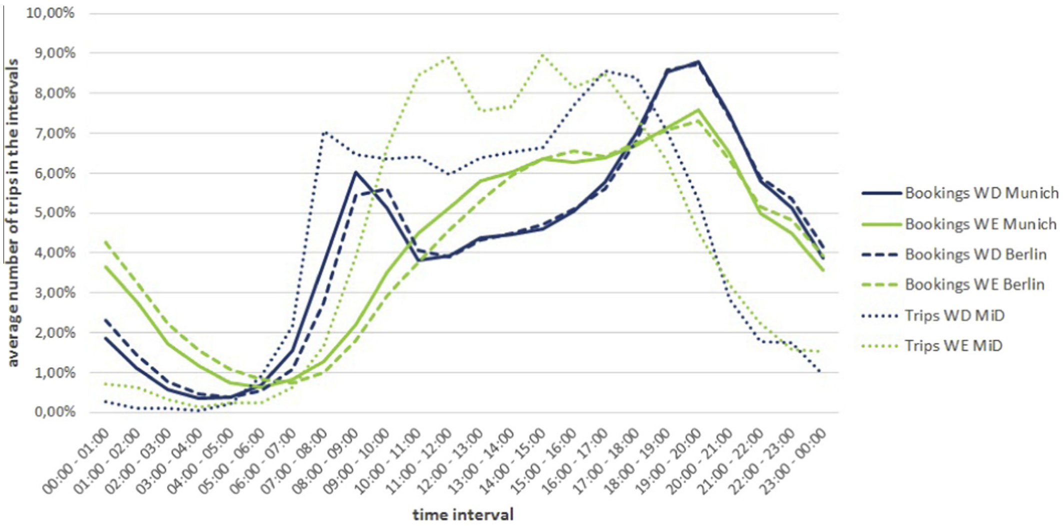


Fig. 7. Average number of carsharing bookings and private car trips in different time intervals on workdays (blue) and weekends (green). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

between 7 p.m. and 4 a.m. is distinctly higher than the one of private car trips. Also, the ratio of carsharing bookings during the night is at least twice as high at weekends, with about 10% of bookings starting between midnight and 5 a.m., whereas the corresponding ratio is approximately 4.5% at weekdays. As before, this distribution shows some differences compared to station-based carsharing (Concas et al., 2013; Leclerc et al., 2013). At weekends, the progression of booking numbers is similar for both types of carsharing but the decline starts later in the evening in free-floating carsharing. On workdays however, station-based carsharing does not show such a distinct peak in the morning hours as observed in this paper. But also comparing the daily curve with the one of a free-floating carsharing system in North America (Kortum, 2012) shows many similarities – such as nighttime booking frequencies – but also one distinct difference: the temporal distribution in (Kortum, 2012) reveals an even higher third peak at noon that is not visible in the graphs in Fig. 7.

Knowing that there are times with lower demand for carsharing by private users might open up new possibilities for operators. On the one hand, they could try to delay all service trips that are not immediately necessary into times with reduced demand. On the other hand, they could also reduce the fleet, freeing up parking space that might be needed otherwise. As free-floating carsharing is mostly operated by car manufacturers, they should have enough capacity (e.g. at local subsidiaries or licensed dealers) to take the vehicles off the streets. This approach, however, causes the problem of bringing cars back onto the street as parking spots have to be found for all these cars.

Reflecting about the distributions of Figs. 6 and 7 also enables to make assumptions about possible trip purposes. As trip purpose data was not available in the given data, all presented assumptions are hypothetical and purely based on the temporal distribution of rentals. Examining the literature about station-based carsharing shows that the most frequent trip purposes are shopping, covering approximately 30% of all trips, social-recreational activities and personal business, with approximately 20% of all trips each (Millard-Ball et al., 2005; Cervero et al., 2007). The two graphs in this paper show some characteristics indicating that the main trip purposes of free-floating carsharing could be similar. On Saturdays and especially on Sundays, it is expected that only a small number of work-related trips take place. Still, Saturday is the day with most rentals and the number of bookings on Sundays is only marginally lower compared to the typical workdays Monday to Thursday. It is very likely that non-work-related trip purposes, such as the ones mentioned earlier, occur very often on those days. Looking at the temporal distribution shows that the afternoon peak at workdays seems to occur too late to be completely work-related especially if considering that the afternoon peak of private car use is reached considerably earlier. Thus, the carsharing peak hour may also include e.g. people going shopping. As the number of bookings is also fairly high after 8 p.m., when most shops and working facilities are closed, it is very likely that free-floating carsharing is also used frequently for social-recreational activities such as going out, visiting friends or doing sports. However, the high number of trips starting late in the day could also indicate that many customers use free-floating carsharing for going home in the evening.

3.2. Spatial analyses

The possibility to make one-way trips is a main characteristic of free-floating carsharing. But how often do customers actually make use of it? In order to answer this question, the ratio of trips with only a short Euclidean distance between starting point and ending point is calculated. To the authors' knowledge, up to now there is no survey about the maximum distance customers are willing to walk to a carsharing vehicle. Because of this lack of knowledge, it is assumed that the value is comparable to the maximum acceptable walking distance to public transport stations. Therefore, a value of 400 m is used in the following calculation as this is claimed to be acceptable, at least in the case of bus stops (O'Sullivan and Morrall, 1996). Assuming 800 m is therefore acceptable for getting to and from a vehicle, each trip with a Euclidean distance of maximum 800 m between start and end is considered as possibly being a round-trip. Of course not each of these trips actually is a round-trip, but it is very likely if the distance covered within a single trip is high and yet start and end are close. On the contrary, it is a reasonable assumption that trips with a high Euclidean distance between start and end are one-way trips. In order to get the ratios of round-trips and one-way trips, the already computed values for Euclidean distance and the given values for trip distances are compared in Table 2.

It can be seen that approximately 11% of all trips in Munich and 8% in Berlin are very likely to be round-trips (the values in italics). The real number may be even higher as sometimes people take the risk and end their reservation despite the fact that they need to return. On the other hand, the values in bold also show that more than 70% of all trips seem to be one-way trips. But the table also shows one somewhat undesirable result. In both cities, more than 6% of all trips cover a distance of zero to one kilometer, a distance that, in most cases, could have been easily made on foot or by bicycle. Maybe operators should try to find a way to reduce this number of short trips if they want carsharing to have an if so, even higher positive impact on the environment.

With this high number of one-way trips, it is also very likely that at times there is an imbalance between where cars would be needed and where the free cars are currently positioned. If an operator wants to adjust such an imbalance by relocating the vehicles, it is important to know where the cars are most likely to be rented in the near future and also where cars can be removed with only a small risk of not being able to fulfill a future request. One possible way to determine these locations is by calculating Hot Spots of usage. Using the booking data, these Hot Spots can basically be determined for any arbitrary time interval. As the starting points of trips are assumed to change over the course of a day (e.g. trips starting at home in the morning vs. trips starting at work in the evening), it is a rational assumption that Hot Spots also shift. In order to confirm this assumption, Hot Spots are calculated for morning hours (here: 6–10 a.m.) and evening hours (here: 5–9 p.m.) both on workdays and weekends. The resulting Hot Spots can be seen in Fig. 8.

In the subfigures, many interesting aspects can be found. At first it is important to confirm that the Hot Spot locations are shifting. Next, it can be seen that the distributions of the Hot Spots show many similarities when comparing workdays and weekends, whereas there are strong differences when comparing morning and evening. Generally, the Hot Spot locations can be classified into four main groups: Hot Spots that occur in every time interval (marked in purple with a dot-dash line), Hot Spots that are more distinct in the morning (marked in blue with a dotted line), Hot Spots that are more distinct in the evening (marked in orange with a solid line) and Hot Spots that are most distinct in the morning at weekends (marked in green with a dashed line). This classification seems to be most appropriate but still it has to be mentioned that even the Hot Spots marked in purple are not equally distinct in each time interval. Trying to find possible explanations for Hot Spot occurrences shows that there may be some similarities in both cities. The areas marked in purple show both a high population density and a high density of shopping possibilities, so this explains why cars are needed in these areas in all the observed time periods. The blue and green areas are mostly residential areas where the highest share of trips is assumed to start in the morning. The yellow areas, in contrast, show a high density of shopping possibilities and many working places paired with a rather low population density; this explains why vehicles are hardly needed in the morning, but very often in the evening.

3.3. External influences on demand

This section deals with the important task of identifying external influences that might have an impact on carsharing demand. The first influence to be investigated is weather, as it is known to have an effect on peoples' choice of transportation

Table 2
Classifying trips by means of distances.

		Traveled distance (Munich)					
		0 km	1 km	2 km	3 km	>3 km	Total
Euclidean distance	⩽ 400 m	1.78%	0.55%	0.42%	*0.50%*	*7.04%*	10.30%
	⩽ 800 m	0.23%	1.50%	0.63%	0.29%	*3.39%*	6.04%
	⩽ 1200 m	0.02%	1.58%	2.15%	0.62%	1.82%	6.19%
	⩽ 1600 m	0.00%	0.48%	3.10%	1.55%	1.78%	6.91%
	⩾ 1600 m	0.00%	0.03%	2.60%	8.74%	59.19%	**70.56%**
	Total	2.04%	4.13%	8.91%	11.69%	73.22%	100.00%
		Traveled distance (Berlin)					
		0 km	1 km	2 km	3 km	>3 km	Total
Euclidean distance	⩽ 400 m	1.72%	0.61%	0.43%	*0.44%*	*5.04%*	8.23%
	⩽ 800 m	0.28%	1.76%	0.66%	0.27%	*2.39%*	5.36%
	⩽ 1200 m	0.02%	1.72%	2.19%	0.53%	1.23%	5.69%
	⩽ 1600 m	0.00%	0.52%	3.27%	1.39%	1.27%	6.45%
	⩾ 1600 m	0.00%	0.03%	2.76%	8.54%	62.93%	**74.27%**
	Total	2.02%	4.64%	9.31%	11.18%	72.85%	100.00%

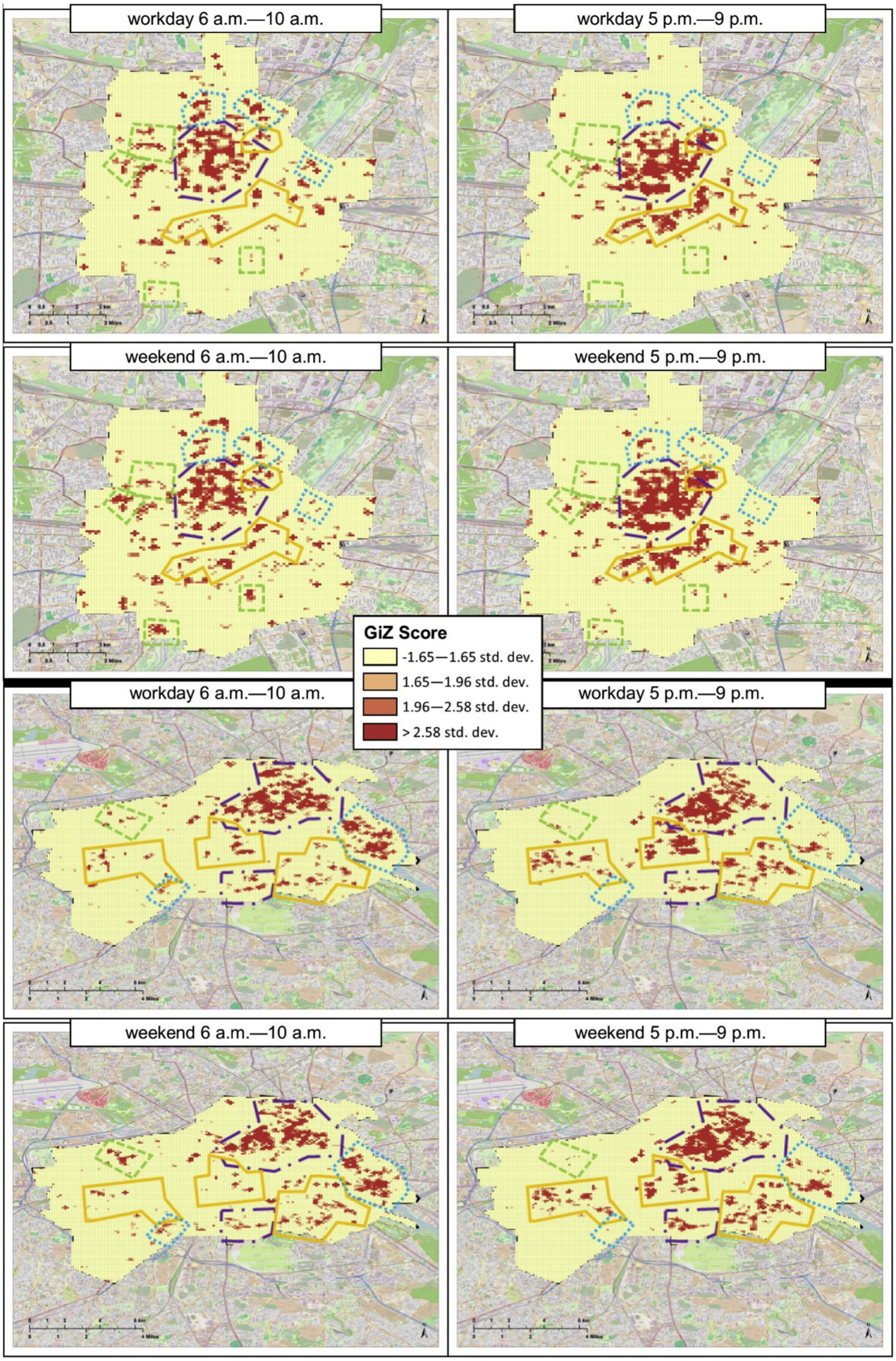


Fig. 8. Hot Spots of free-floating carsharing usage in Munich (top) and Berlin (bottom) at different times.

mode (Sabir et al., 2007). As weather forecasts are most reliable on a short horizon, the influence of weather on carsharing usage is also assumed to be short-term. As observed in Schmöller and Bogenberger (2014), there is no significant impact when looking at the correlation between booking frequencies of whole days and the corresponding average temperature or total amount of rainfall on that day. But as free-floating carsharing can be used at short notice, there might actually be an impact when the weather changes in the course of the day as people have the possibility to react on this change.

3.3.1. Short-term influence by weather

Changes in current weather can be measured either in temperature or in the amount of precipitation. As the authors assume that temperature changes have a lower effect on a person's mode choice, only precipitation is examined here. Furthermore, weather changes are in general assumed to have a higher effect when they occur in the afternoon (in contrast to the morning, when the authors assume the current weather condition to be a driver on mode choice). For this reason only bookings in the afternoon are considered. Since carsharing usage varies between the different days, only Monday to Thursday are considered in the following because both total number of bookings and daily progress are comparable on these days. This means days with higher usage or a different daily curve are not overrepresented in the set of days with precipitation and will not bias the results. In order to show that changes in weather conditions can lead to higher carsharing demand, two time slices of equal length are evaluated. One is the workday peak (from 5 p.m. to 8 p.m.) and the other is the period just prior to it (from 2 p.m. to 5 p.m.). Due to a limited availability of weather data (MingaWeda, 2015), the calculations are performed only for Munich and restricted to the period starting from January 2, 2012. In the following, it is only differentiated between time slices with any precipitation occurring within the time interval and time slices with no precipitation at all. This is an intentional decision because it is unknown how much precipitation is necessary to influence mode choice. Each day is then classified by its combination of weather conditions in the two time intervals. Table 3 shows for each possible combination the quotient between the total number of bookings between 5 p.m. and 8 p.m. and the total number of bookings between 2 p.m. and 5 p.m. on the corresponding days is shown in Table 3. This shows whether days with changing weather conditions correspond with an increased or decreased number of bookings in the second time interval.

This table indicates an influence of weather changes on booking frequencies. The quotient between bookings in the evening and bookings in the afternoon is about 6% higher than the average when it starts to rain in the evening. It is therefore assumed that people react to this kind of change. This result may be useful for operators as they could try to make service trips during dry afternoons when demand is low anyway and redistribute the cars when rainfall is forecast.

3.3.2. Long-term influence by socio-demography

The next step in the prediction of demand is achieved by looking at long-term influences. These are needed for estimating the profitability of starting up carsharing in new cities or for future enlargements of the operating area. By now, the most promising approach for this kind of prediction is provided by searching for a relationship between socio-demographic data and booking frequencies. In the presented paper this correlation is examined by applying linear regression models. The variables included in the data are narrowed down to the ones that seem to be most appropriate, since not all variables are applicable in the presented case (such as distance to the next airport; in Munich, the airport is about 30 km outside the urban area and will most likely have no influence on the spatial distribution of carsharing usage). As not all the variables in the data set yield useful results, just the ones resulting in an R^2 of at least 0.1 in one of the cities are shown in Table 4. The second and third column show whether the tested variable had a positive or negative impact on the number of bookings in the corresponding city. A plus (minus) means that a higher value in the tested variable results in a higher (lower) number of bookings, and "n.a." shows that the corresponding variable seems to have no structurally significant influence on booking numbers.

This table shows that those variables which are based on the areas' demographic structure are most suitable for describing the booking frequencies. Yet there also are age classes ($18-29$ and $50-64$) that have been tested but do not appear in the table because their coefficient of determination is below 0.1. Interestingly, the age classes with highest influence differ between the two cities. In Munich, the highest (positive) correlation is given in the percentage of persons between 30 and 39 years of age whereas in Berlin this applies for persons between 40 and 49 years of age. Another important point in this table can be observed in the direction of the correlations. Even if the R^2-values strongly differ between the two cities, the direction of the variables is identical in both Munich and Berlin. The socio-demographic results also comply with the results

Table 3
Quotient between bookings on early evenings and bookings on afternoons under different weather conditions.

Average normalized number of bookings		5–8 p.m. No precipitation	5–8 p.m. Precipitation	5–8 p.m. Average
2–5 p.m.	No precipitation	1.608 (288 days)	1.705 (28 days)	1.616 (316 days)
	Precipitation	1.580 (25 days)	1.586 (43 days)	1.584 (68 days)
	Average	1.605 (313 days)	1.627 (71 days)	1.609 (384 days)

Table 4
Coefficients of determination for several socio-demographic aspects.

Variable	±MUC	±BER	R^2 MUC	R^2 BER
Number of companies per km^2	+	+	0.3403	0.1269
Number of persons 35–39 years of age as a percentage of total population	+	n.a.	0.2725	n.a.
Number of persons 30–34 years of age as a percentage of total population	+	n.a.	0.2646	n.a.
Number of persons 45–49 years of age as a percentage of total population	+	+	0.1593	0.2437
Number of persons 40–44 years of age as a percentage of total population	+	+	0.1602	0.2361
Rent price ratio	+	+	0.2258	0.1534
Number of persons at least 75 years of age as a percentage of total population	–	–	0.1592	0.1806
Number of single person households as a percentage of total number of households	+	n.a.	0.1738	n.a.
Number of persons 65–74 years of age as a percentage of total population	–	–	0.1729	0.1362
Number of households that claim to place a high value on material things as a percentage of total number of households	n.a.	+	n.a.	0.1546
Number of two-person households as a percentage of total number of households	–	n.a.	0.1539	n.a.
Number of employees subject to social insurance contributions as a percentage of total population	+	+	0.1143	0.1229
Number of DINK households (dual income no kids) as a percentage of total number of households	–	–	0.1308	0.0815

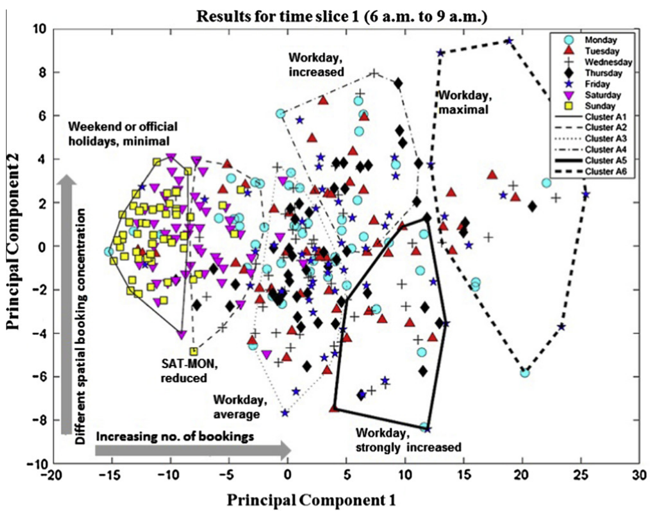
of Millard-Ball et al. (2005) for station-based carsharing. Once again it appears that users of free-floating carsharing mostly are young people who live in small households (in the presented case especially single households as two-person households have a negative effect). Two more findings are of note even if they do not refer to the users: First, the number of companies per km^2 (containing huge employers as well as shopping facilities or bars, restaurants, etc.) has a positive – in Munich even the highest – impact. Second, how high rents are also has a positive influence: in areas with higher rents, the number of bookings is also higher. These results again comply with the calculated Hot Spots in Fig. 8, in which it was shown that most Hot Spots coincide with residential areas or areas where many companies are located.

3.4. Spatiotemporal analysis of demand

Both the temporal and the spatial aspects of demand have already been examined independently. As there is often an interaction between those two factors, this section combines them in a spatiotemporal analysis.

3.4.1. Spatiotemporal cluster analysis of carsharing bookings

The cluster analysis described in Section 2 is used to identify six groups of two-dimensional points in each time slice. Each of these points can still be ascribed to an originally ten-dimensional vector. Therefore, it is also possible to reconstruct the number of bookings, their distribution over the ten zones and the day on which they occurred. With this knowledge, it is possible to interpret the two principal components. Representing each day with a different color and shape makes it easier to identify the six different clusters as shown in Fig. 9 for the time slice between 6 a.m. and 9 a.m. Looking at the booking numbers shows that horizontal displacements are associated with different booking frequencies (increasing from left to right) and using their distributions shows that vertical displacements are associated with a different distribution over the



Cluster	Number of days	Relative deviation from overall average booking number in cluster	Description
A1	81	-69%	Weekend or official holiday with minimal demand
A2	57	-31%	Reduced demand, mostly Saturday to Monday
A3	111	+8%	Workday with average demand
A4	52	+30%	Workday with increased demand
A5	38	+55%	Workday with strongly increased demand
A6	27	+101%	Workday with maximal demand

Fig. 9. Result of the principal component analysis and interpretation of the identified clusters.

FROM/TO Cluster	B1	B2	B3	B4	B5	B6
A1	16%	40%	26%	5%	14%	0%
A2	14%	19%	12%	11%	28%	16%
A3	9%	40%	16%	27%	5%	3%
A4	2%	15%	40%	23%	17%	2%
A5	0%	11%	18%	29%	34%	8%
A6	0%	0%	4%	11%	48%	37%

Cluster	Number of days	Relative deviation from overall average booking number in cluster	Description
B1	32	-49%	Strongly reduced demand, mostly Sunday to Thursday
B2	99	-25%	Reduced demand, mostly Sunday to Thursday
B3	75	-2%	Workday or Weekend with average demand
B4	66	+/-0%	Workday with average demand
B5	68	+34%	Increased demand, mostly Friday and Saturday
B6	26	+69%	Strongly increased demand, mostly Saturday

Fig. 10. Frequency of transitions between the clusters of time slice 1 and time slice 2.

ten areas. The clusters identified by MATLAB are then distinguished in terms of their distribution among the different workdays. Additionally, for each cluster, the average number of bookings in the specific time interval and its deviation from the average number of bookings over all days in this time slice were calculated. Thus it is made possible to identify booking clusters with reduced, average, or increased number of bookings in each time slice (see right part of Fig. 9 for time slice 1).

One possible objective of the cluster analysis is a short-term prediction of future demand. For each time slice, the development of the clusters in the next time slice is thus identified. As an example, consider the development of the six clusters from time slice 1 (6–9 a.m.) to time slice 2 (9–12 a.m.). For each cluster in time slice 1 (the clusters A1–A6), it is calculated how the corresponding days are distributed over the clusters in the next time slice (the clusters B1–B6). These distributions and the identifications of the clusters in time slice 2 are shown in a From-To-Matrix in Fig. 10.

In order to give an example, the 40% from A3 to B2 are considered. This shows that 40% of the days that were found in cluster A3 in time slice 1 (workdays with average demand) are then retrieved in cluster B2 in time slice 2 (Sunday to Thursday, with reduced demand). This approach can be repeated for all the other transitions between two different time slices and possibly helps to predict future demand on a short-term basis.

3.4.2. Identification of carsharing demand phenomena

As shown in Fig. 6, Mondays exhibit the lowest number of bookings in both cities, whereas booking numbers increase over the course of the week. However, the cluster analysis showed that weekends and official holidays have minimal booking numbers in time slice 1 (6–9 a.m.) as bookings mostly start later on those days, as seen in Fig. 7. It is also noticeable that cluster A2, with a reduced number of bookings, contains a higher number of Mondays compared to other workdays. Moreover, Mondays spread more strongly among the different clusters in time slice 1 than the other workdays.

This scattering is assumed to be caused by an imbalance between the locations where the cars are left on Sundays and where they are needed on Mondays. In order to test the existence of this imbalance, the deviation between supply of and demand for cars available is measured. First, the average spatial vehicle distribution at 6 a.m. (the beginning of time slice 1) is calculated for those Mondays in cluster A2 with reduced booking numbers. Therefore, for each of the 10 zones of the operating area, the average number of available vehicles on those Mondays at 6 a.m. is calculated. The average vehicle distribution of those Mondays is shown top left in Fig. 11. In order to derive the degree to which this distribution of vehicles deviates from the actual demand on workdays, cluster A6 of workdays with maximal booking numbers is analyzed. For each of the 10 areas, the average number of bookings of this cluster is calculated. The result is the average spatial booking distribution of the workdays with maximal booking numbers in this time slice. The corresponding percentages are shown bottom left in Fig. 11. Afterwards, this booking distribution of the maximal cluster is compared with the calculated initial vehicle distribution on Mondays with low utilization. In doing so, a higher percentage of the number of vehicles per zone compared to the number of bookings indicates a vehicle oversupply, whereas a lower percentage indicates a vehicle shortage. This is shown top right in Fig. 11. The bar plot (bottom right of Fig. 11) shows that on the "weak" Mondays in cluster A2 in time slice 1, the percentages of supply and demand are almost balanced in zone 4. The southern zones 2, 5 and 7 exhibit a vehicle oversupply of approximately 2%, 1% and 2%. The oversupply is even more significant in the zones 1, 3 and 6 with percentages of 6%, 4% and 3%. In contrast, the northern zones 8, 9 and 10 show a vehicle shortage with 7%, 4% and 6%. Thus, an asymmetry between the northern part and the southern part (see red line in Fig. 11) of the operating area is identified. Vehicles concentrate in the south of the operating area in the course of the weekend but they would be needed in the northern part on Monday.

In order to identify the reasons for the observed imbalances between supply and demand, the areas with vehicle oversupply are once again examined with regard to their location and their characteristics. When considering the socio-demographic data again, it is seen that the zones 1–7 have a rather low density of population and companies. The oversupply of vehicles in those areas is thus likely to be caused by (one-way) leisure trips during the weekend. In contrast, zones 8–10 with vehicle shortages exhibit higher densities of population and therefore a higher number of potential customers' homes.

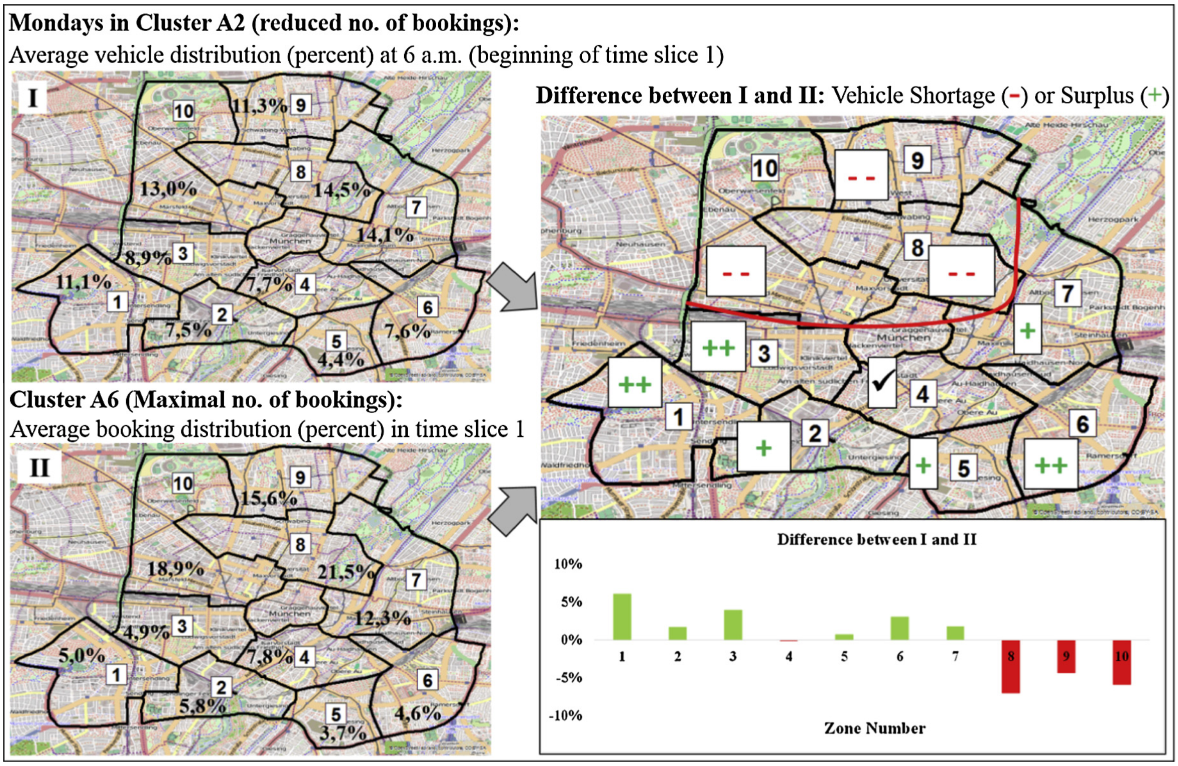


Fig. 11. Comparison between the average vehicle distribution on ''weak'' Mondays in cluster A2 and the average booking distribution of the maximal cluster A6.

4. Conclusions and outlook

This paper provided a deep insight into the usage of free-floating carsharing. Both temporal and spatial aspects of demand were illuminated, showing that it is mostly concentrated on a few temporal peaks and spatial Hot Spots. Looking at the temporal demand showed that there are weekdays and time intervals with significantly higher booking frequencies. Analyzing spatial demand showed that it is mostly concentrated within a few areas. Combining both aspects in a spatiotemporal analysis revealed that there is an asymmetry between vehicle demand and supply on Mondays, necessitating intervention in the form of vehicle relocations by the operator. With the knowledge that the placement of areas with highest demand depends on the city structure and varies over time, an operator might be able to improve his service. For instance, he could use times with reduced demand for making service trips and, by knowing the locations of Hot and Cold Spots at different times, could make his relocation strategy more efficient. Another result that could help improve the service has to do with how changes in the weather can have an impact on the booking frequency. By using reliable weather forecasts, operators could move cars to places where they are most likely to be needed and aid people responding to changing circumstances. At last some socio-demographic characteristics of free-floating carsharing users have been derived. Knowing where potential customers live is important for operators wishing to expand services into new parts of a city or into additional cities.

As this paper was a first attempt to analyze booking data on such a large scale, it is obvious that there are still possibilities to improve the utilized methods. Although the resulting Hot Spots seem to be reasonable and show some interesting aspects, it might also be interesting to calculate the Hot Spots of trip endings as the destination of a trip is assumed to be a better indicator about the trip purpose. Another possible way of improvement is found on the technical side. It might be better not to use a net of square cells since only the four direct neighbors sharing an edge are considered in the presented approach. This analysis could eventually be improved by using a net of hexagons instead. This way, each neighbor sharing an edge or vertex is considered and all of them share the same distance to the currently considered cell.

The correlation between booking numbers and socio-demography is currently on a low level but there may also be some possibilities to improve the results. One way could be to not only look at the area where the booking started but also into the surrounding areas as long as they are within a reasonable distance (such as the 400 m that customers might be willing to walk to a carsharing vehicle). Another drawback is the restriction on starting points. As described in the Hot Spot analysis, it is very likely that trips that are made in the evening do not begin at home. There might be some potential for reaching higher correlations to socio-demographic data when looking at endings in the evening.

Possibly, the presented results can be used as a basis for other researchers. The calculation of environmental effects of free-floating carsharing may yield more reliable results when knowledge about actual usage is factored in. The same applies for simulation models including carsharing. Using information about when and where the system is used most frequent could help calibrate a model and therefore improve results. On the other hand, not all the presented results are applicable for immediate use. Even if the approach for describing socio-demography yields a higher correlation using the suggested improvements the results must not necessarily be satisfying. In order to confirm or disprove the results, there is still the need for a survey exploring the socio-demography of customers of free-floating carsharing. In combination with the presented results such a survey could make an important contribution towards providing as complete a picture as possible of free-floating carsharing users and usage.

Since it is assumed that the demand for carsharing will continue to increase, research on this area will be pursued in the future. The analyses of this paper will be extended after more data is available, especially of further cities. This will facilitate identifying recurring patterns over several years in different cities. Furthermore, the influence of weather and socio-demography will be analyzed in more detail in order to establish short-term and long-term prediction models.

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