Spatial and temporal analysis of bike-sharing use in Cologne taking into account a public transit disruption

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Abstract: This research analyzes the relationship between bike-sharing and public transit using bike-sharing data collected in Cologne, Germany. The selected system is one of very few in Germany that is organized as a free-floating system, which allows the generation of more detailed data. A construction site in the light rail network causing multiple disruptions in the public transit network offered the possibility to detect changes in bike-sharing usage that occur in the corresponding period. Applying negative binomial regression, spatial and temporal usage patterns are analyzed to identify connections to the public transit network and other factors influencing the usage of bike sharing. The analysis suggests the existence of a spatial relationship between bike-sharing and public transit. Therefore, an intermodal use of both means of transport can be assumed. The short-term changes in the public transit network caused by the construction site only have minor impacts on the usage patterns. Other factors that affect the usage structures could be identified. Proximity to universities as well as the number of certain points of interest nearby, such as food outlets and shops, promote bike-sharing use. Higher temperatures are also positively correlated, while rain reduces usage. The findings of the study can be beneficial to integrate bike-sharing into urban transport systems, especially regarding public transit.

Keywords: Bike sharing; Public transport disruption; Negative binomial regression; Spatiotemporal analysis

1 Introduction

During recent years, bike-sharing systems (BSS) have emerged in many cities and regions of Germany and around the world as an additional element of the urban transport system. As of early 2020, bike-sharing is offered in more than 2,100 cities worldwide, comprising a total of almost 18 million bicycles (Meddin and DeMaio, 2020). Bicycles can be rented at short notice, flexibly, and for short periods (Midgley, 2011: 1). In addition to using a bicycle for a round trip, it is possible to travel only certain trip stages by bike, thus encouraging intermodal trips. Especially a combination with public transit can offer certain benefits and is therefore regularly pursued in the planning of BSS.

The generation of data by BSS offers unique possibilities to monitor and evaluate spatial and temporal usage patterns. This also allows us to determine whether a measurable relationship exists between bike-sharing and public transit and helps to draw conclusions for planning. There is a range of studies that analyze bike-sharing data to understand usage and implications for urban transport systems, to improve and facilitate planning or the relocation of bicycles. Geography, and especially this journal, play a prominent role in this debate (Xie and Wang, 2018; Liu and Lin, 2019; Younes et al., 2019; Wang and Chen, 2020). Previous research was focused mainly on dock-based systems that collect trip data between docks. So far, there are few publications dealing with BSS organized as free-floating systems that allow bicycles to be rented and parked flexibly within the operating area (Li et al., 2019a; Li et al., 2019b; Yang et al., 2019). In Cologne, public data is available for the free-floating BSS operated by nextbike (Stadt Köln and DKAN, 2019). The form of organization distinguishes this system from most other BSS in Germany that are organized using docks. Thanks to the level of detail in the generated data, we can identify the origins and destinations of trips (or trip stages) much more precisely.

As previously mentioned, the relationship between bike-sharing and public transit has attracted particular attention from operators and previous research. Still, there are relatively few publications that look at the impact of disruptions in the public transit system on the use of bike-sharing, as these events are rare (Kaviti et al., 2020; Fuller et al., 2019). By evaluating the use over the observation period and comparing the time ranges before, during and after construction work on the light rail network, changes in use can be discovered. This is what the present paper does. The results thus provide further insights into the relationship between bike-sharing and public transit. We use descriptive statistics to present bike-sharing use before, during and after the disruption in the vicinity of stations that were affected in different ways by the construction work. Additionally, we carry out two negative binomial regression models that estimate the number of bike-sharing trips based on a range of potential spatial and temporal factors, respectively. In this way we attempt to further advance research on BSS use from a geographical, spatiotemporal perspective. Also, the analysis allows us to draw conclusions about potential user groups of the BSS. To the best of our knowledge, this is the first detailed study on BSS use from a spatial and temporal perspective in Germany.

The remainder of this paper is structured as follows. Section 2 explains the relationship between bike-sharing and public transit, gives an overview of current literature analyzing bike share data, and presents the state of research on factors influencing bike share usage. In Section 3, the study area, data and methods are introduced. The results of the analysis are presented in Section 4. Finally, planning conclusions are derived from the results in Section 5.

2 State of the research

2.1 Bike-sharing and public transit

Connections between bike-sharing and public transit have generally been recognized in research and practice. The implementation of bike-sharing can complement the public transit system by closing gaps in the network (Shaheen et al., 2010: 2; DeMaio, 2003: 10; Monheim et al., 2011: 80). Bike-sharing can offer an alternative means of transport during the rush hour, when demand exceeds capacity, or when there is no public transit service available or the frequency is low, especially at night (Büttner et al., 2011: 42; Zademach and Musch, 2016: 187; Monheim et al., 2011: 83). The most important use of bike-sharing as a complement to public transit is that it offers a solution for the last mile. Zhang and Zhang (2018) observe that persons with a higher rate of public transit use tend to practice bike-sharing more frequently.

On the other hand, it can be argued that bike-sharing systems may compete with public transit. Both systems may attract those who have no private car available. Hence, bike-sharing may reduce public transit ridership especially in cases where public transit is less attractive than renting a bike, e.g. on short trips that are typically covered by bus rather than rail, where waiting times account for a large share of total trip time or when operational speed in public transit is low (Zhang and Zhou, 2019; Ma et al., 2019; Böcker et al., 2020).

At least three ways to integrate bike-sharing into public transit systems are discussed in the literature. Firstly, information for both systems can be displayed in combination. Secondly, spatial integration describes the creation of bike-sharing docks at public transit stations. Thirdly, tariffs can be integrated by allowing customers to pay for both modes simultaneously, sometimes even offering special conditions for users of public transit (Büttner et al., 2011: 58,26).

There are several studies dedicated to the quantification of this relationship. Tran and Ovtracht (2018) as well as Zhao et al. (2019) find evidence for a spatial association by analyzing user data. They observe an increased usage of BSS in closer proximity to public transit stations. According to Mobike, one of the largest bike-sharing operators, 90% and 81% of all trips in Shanghai and Beijing, China, respectively, start within 300 m of a bus station; 51% and 44% start within 500 m of subway stations (Mobike, 2017). Sun et al. (2017) detect a correlation of bike-sharing use with public transit frequency.

2.1.1. Disruptions in public transit

Events that change the availability of public transit and their effects on travel behavior have been studied in recent years (Kaviti et al., 2020; Fuller et al., 2019). Such events can either be permanent changes through the opening or closure of lines, or temporal disruptions due to construction work or strikes. They can reveal more information about the interactions between public transit and bike-sharing. Yang et al. (2019) observe an increase in the number of bike-sharing trips after the opening of a new underground line in Nanchang, China, especially in the area surrounding new stations. At the same time, the average distance traveled decreases (ibid.: 7). Studies that examine the influence of temporal disruptions in the public transit network over time typically find that bike-share usage increases during these events but returns to the initial level after the public transit systems resume normal operations (Kaviti et al., 2020; Younes et al., 2019; Fuller et al., 2019).

2.2 Other factors that affect bike-sharing use

Apart from public transit, there is a range of factors that have an impact on the use of BSS. Among them are various characteristics of the transport system. A well-developed system of bike lanes and other bicycle infrastructure increases the use of bike-sharing (Wang and Chen, 2020; Tran and Ovtracht, 2018; Sun et al., 2017).

Land use is strongly connected to bike-sharing as well (Liu and Lin, 2019; Faghih-Imani et al., 2014). In general, the traffic demand generated in an area is closely related to the densities of population and jobs (Büttner et al., 2011: 45; Wang et al., 2015; Tran and Ovtracht, 2018; Zhao et al., 2019; Sun et al., 2017). This means that bike-sharing should be offered especially in the vicinity of places that create large amounts of trips, such as universities, important employers or train stations (Monheim et al., 2011: 150). However, smaller trip generators in a city also have a measurable impact on bike-share trips. Several studies recognize a positive correlation between the number of trips and the number of certain points of interest, such as restaurants (Wang et al., 2015; Wang and Chen, 2020; Zhao et al., 2019). Bike-sharing is mostly offered in city centers, because here demand meets a critical level and trips are generally short, promoting bike use. Therefore, bike-share usage increases along with proximity to the city center (Wang et al., 2015). Furthermore, usage increases in proximity to water bodies (ibid.).

Some studies tackle the question of how bike-sharing users can be characterized. They detect negative correlations between the shares of children and senior residents, respectively, in the population and bike-share usage (ibid.). Additionally, an influence of gender, income, household size, car ownership and BMI can be found (Barbour et al., 2019).

In most BSS, demand changes over the course of a year, depending on the climate. In warm countries, the highest number of trips are recorded in spring and fall (Büttner et al., 2011: 32). In Germany, bicycle usage reaches peaks in June and September, decreasing considerably during winter, with a minimum in January and February. Additionally, short-term weather events like rain and snow have a negative impact on bike-sharing (Gong and Yamamoto, 2019). Gebhart and Noland (2014) state that trips that can be replaced by public transit are more negatively affected by poor weather. They also detect negative effects of darkness and humidity on trip number and length. Zhou (2015) finds that the temporal distribution of trips on working days is similar to the general travel pattern and the highest use can be observed during the rush hour. On weekends, usage numbers are considerably lower.

2.3 Empirical analysis of bike-sharing

In recent years, the number of studies focusing on bike-sharing has risen simultaneously with the spread of BSS in cities worldwide. Romanillos et al. (2016) offer a comprehensive overview of studies that deal with this topic. They identify three groups of data used: GPS data, live point data and journey data.

Authors apply a range of different methodologies and approaches to analyze bike-sharing data. Calculation of descriptive statistics helps to assess the temporal and spatial qualities of BSS (Li et al., 2019a; Xie and Wang, 2018; Purnama, 2018; Romanillos et al., 2018; Hu et al., 2019). For BSS that include docks, cluster analysis is a regularly applied method. Origin-destination matrices can be generated to cluster bike-sharing stations according to use patterns (Vogel et al., 2011; Zhou, 2015; Zhang et al., 2017; Shi et al., 2019; He et al., 2018). Clustering is also applied by Liu and Lin (2019), Froehlich et al. (2009) and Li et al. (2019b). Another method is the identification of hot and cold spots (Zhang et al., 2016; Cheng et al., 2019; Keler et al., 2019).

In line with the methodological approach of this research, applications of regression analysis of bike-sharing data are presented in the following, with a focus on those that examine the relationship between bike-sharing and public transit. Wang et al. (2015) conduct OLS regression to identify factors influencing the use of bike-sharing stations in Minneapolis, USA, focusing on the impact of businesses and jobs. Tran and Ovtracht (2018) model the total number of departures and arrivals at bike-sharing stations in Lyon, France, in a linear regression analysis depending on public transit and BSS characteristics and socio-economic, topographic and recreational variables.

Kaviti et al. (2020) investigate the impact on the usage of bike-sharing of the introduction of a new fare option in the BSS of Washington, D.C., USA, in combination with the closure of subway stops during several periods of construction. Using t-tests, differences in the number of bike-sharing trips within a 0.25- and 0.5-mile radius around the affected stops are determined one week before, during and after the construction work. In addition, linear regression is calculated to determine the effect of the tariff change.

Due to the nature of the generated data, the requirements for the application of linear regression are regularly not met and Poisson and negative binomial regression analysis are applied. Zhao et al. (2019) use a zero-inflated negative binomial regression to model the redistribution needs of BSS stations in Nanjing, China. As independent variables, they consider points of interest (POI) by different categories, weather, public transit stations, demographic and smart card data. Six separate models, each for one time of the day, are calculated. Wang and Chen (2020) use a zero-inflated negative binomial model to estimate the number of hourly arrivals at bike-sharing stations and station capacity in New York City, USA, as a function of cycling infrastructure, land use and POI, public transit and temporal and weather data. Gong and Yamamoto (2019) identify, firstly, temporal influence factors for the total number of journeys in New York City using multivariate linear regression and, secondly, spatial influence factors for the trip counts of individual census tracts using negative binomial regression analysis. Separate analyses are conducted for workdays and weekends.

Gebhart and Noland (2014) study the effects of weather on trips made with the BSS in Washington, D.C. They consider the number of trips per hour over a 15-month observation period as dependent variables in a negative binomial regression. The average length of the trips is analyzed using an OLS model. They pay special attention to journeys whose start and end points are both located in a ¼-mile buffer around metro stations.

3 Methods

3.1 Research area

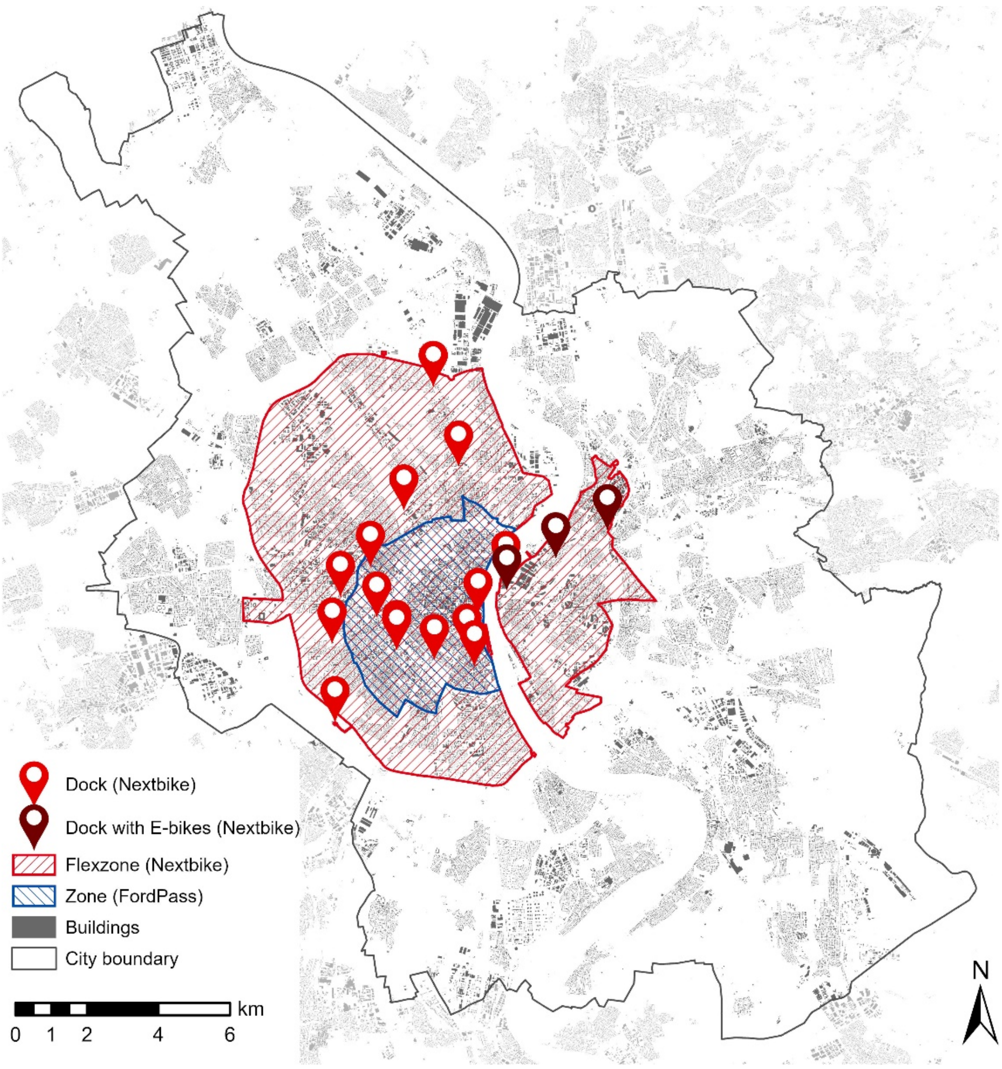
For this research, the city of Cologne was chosen because it provides an opportunity to analyze one of the few free-floating BSS in Germany. The city has about 1.1 million inhabitants (Stadt Köln, 2019b: 11) and extends over an area of 404.89 km² (ibid.: 9). Cologne is a well-known tourist destination and fulfills important economic and administrative functions for the whole region. About 270,000 people commute into the city and about 121,000 residents commute to other cities. A range of different universities and colleges attracts about the 100,000 students who live in the city (ibid.: 239). In recent years, the population has increased steadily (Stadt Köln, 2019a: 8).

Due to its central functions and location on major routes, Cologne represents a transport hub that accommodates both urban and inter-urban traffic (Stadt Köln, 2014: 12). The public transit network is well-developed and consists of light rail and buses, carrying about 280 million persons per year. There are two main stations, connecting the city to regional and long-distance trains. The share of cycling in the modal split of Cologne has increased in recent years, amounting to 18% in 2017 (Nobis, 2019: 57). 46% of all residents use a bike at least once a week (ibid.: 52). Intermodal mobility options are promoted by the city. There are 40 Park+Ride stations on the outskirts of the city and in neighboring municipalities (Stadt Köln, 2014: 7). A large number of bicycle parking facilities with a total of more than 14,300 parking spaces at rail stations allow changes between bicycle and rail to be made (Stadt Köln, 2016).

Currently, there are three different bike-sharing operators present in the city, all organized without permanent docks and running about 4,000 bikes in total. 1,450 of these bicycles are operated by nextbike, whose data is analyzed in this study. Additionally, the nextbike BSS includes a very small number of pedelecs. Scooters are not part of this BSS, but there are several companies offering scooter rental in Cologne. The BSS has existed since May 2015 and is operated in cooperation with the public transit operator KVB (Anemüller, 2017). The area covered by the system, called flexzone, amounts to 84 km² in the central districts of Cologne on both sides of the Rhine (Figure 1). The figure also shows the small zone covered by FordPass, another bike operator. There is no information available on the service zone covered by Mobike, a third competitor. The bicycles included in the nextbike BSS are used 1.2 million times a year, with 3,000 – 3,700 trips per day (ibid.). The system had 110,000 registered users in 2018 (Kölner Verkehrs-Betriebe AG, 2019: 32). Although the BSS is organized as a free-floating system, there are 17 additional docks. Pedelecs can only be rented at three of them. The BSS specifically aims to provide a last-mile solution to improve access to destinations that cannot be reached directly by bus or train, or where public transit frequency is insufficient (Anemüller, 2017).

Although nextbike allows customers to flexibly drop off the bikes within the flexzone, several rules have to be respected: drop off on private property or in parks is not allowed and is subject to a service fee (nextbike GmbH, 2020c). These regulations are strongly influenced by the quality agreement for bike-sharing that was created by the city administration in 2018 to prevent conflicts with other road users (Verkehrsausschuss, 2018).

Figure 1: Map of Cologne and the zones of Bikesharing operators



Data: Stadt Köln, 2020; Deutsche Bahn AG, 2020; OpenStreetmap

Season ticket holders for public transit and university students are offered free rides of up to 30 mins (nextbike GmbH, 2020a; nextbike GmbH, 2020b). As a result, these groups make up a large proportion of users: 32% of users are job ticket holders and 43% are students with a semester ticket (Anemüller, 2017). Besides, the tariff promotes short trips, so that only 8% are longer than 60 mins (ibid.).

3.2 Data

The bike-sharing data analyzed in this study were retrieved from https://offenedaten-koeln.de (Stadt Köln and DKAN, 2019). The current locations of all bicycles of the BSS that are not in use can be assessed through an API. The website limits access to the locations to once in 10 mins.

This dataset was saved automatically every 15 mins using an Excel VBA script throughout the whole observation period, which lasted from September 30th, 10:46 am until November 4th, 10:49 am, 2019. This period was chosen because it included two events of interest: firstly, the beginning of the winter term at the Cologne universities (October 7th) and, secondly, a public transit disruption that resulted from construction work at important stations on the Cologne inner-city light rail network between October 13th, 8:00 pm and October 28th, 3:00 am. During this time, some stations were closed and several lines were diverted. Stations that were not closed completely but where at least one regular line was canceled due to diversions are referred to as semi-closed. The period chosen also means that our data are not representative for the year as a whole, as an above-average number of students may be in the city at the beginning of the universities' winter term.

The chosen 15-min intervals for data retrieval imply that we may have missed some trips, especially short trips when two or more loans occur directly one after another within 15 mins. This should result in an overestimation of trip distances. However, we consider this a minor issue as the average distance we calculated is even somewhat shorter than those recorded in other German case studies (2.1 km straight-line distance averaged for six case regions, Rabenstein, 2015; our study: 1.74 km) while both estimations fit reasonably well.

The data saved amounts to about 3,300 separate files. These are combined in a single table that contains the recorded locations of all bikes by ID. In the next step, changes of location that indicate completed trips can be identified. The few spatial outliers (trips including an origin or destination outside of Cologne) are removed. The files included 2,528,567 locations of bicycles within Cologne (after excluding 14,398 locations outside of Cologne). To exclude changes in location caused by the rearrangement of parked bikes or slight inaccuracies in position measurement, 100 m was chosen as the minimum trip distance (following Yang et al., 2019). After eliminating all trips shorter than this, 76,859 trips remain. Our data do not allow us to determine whether a change of location might be due to service staff. As most bicycles are typically located at highly frequented places in the flexzone we believe that this does not cause major problems.

The independent variables used are the locations of public transit stops and major arterials, the land use plan of Cologne, locations of universities, green spaces, and most POI (schools, kindergarten, libraries, hospitals, public administration, museums, tourist attractions, venues). Most can be obtained through https://offenedaten-koeln.de. Additional POI were extracted from Open Street Map data (download.geofabrik.de). Data from the most recent 2011 census are used as sociodemographic variables and can be accessed through https://www.zensus2011.de. An additional dataset from https://gdz.bkg.bund.de of the Federal Agency for Cartography and Geodesy is used to connect the data with the corresponding grid cell. Historical weather data in an hourly resolution is provided by Germany's National Meteorological Service (DWD) and can be obtained from https://opendata.dwd.de.

3.3 Modelling approach

To analyze the influence of a public transit disruption and other urban characteristics on the use of bike-sharing, we carry out a negative binomial regression in R statistics, version 3.6.3, that is suitable for count response variables. We estimate two cross-sectional models (1) using the number of trips that started within a certain area, regardless of time, and (2) a model using the number of trips that started within a certain period regardless of place ('time-related' model) as response variables. The reason for estimating separate models is that extremely low goodness of fit results from a negative binomial regression analysis of combined spatiotemporal counts including spatial and temporal variables.

Another popular regression method for count data is Poisson regression. Our variables display overdispersion, as variances considerably exceed means (Fahrmeir et al., 2009: 197). We perform the odTest from the package pscl in R that evaluates at a significance level of 5% whether the assumption of the Poisson distribution of equality of expected value and variance is violated (Wollschläger, 2014: 314). For the models used in this research, test results are significant. This means that Poisson-distribution cannot be assumed and negative binomial regression should be chosen as the adequate model. The density function is modified so that the expected value is still: $E(y) = \lambda$. However, the variance is linked to it as follows (Wollschläger, 2014: 313):

$$Var(y) = \lambda + \frac{\lambda^2}{\theta} = \lambda\left(1 + \frac{\lambda}{\theta}\right)$$

Thus, the variance can be adapted by choosing a suitable θ (ibid.). θ is also referred to as the dispersion parameter (ibid.: 314).

The regression analysis is carried out in R using the function glm.nb from the package MASS. First, an estimate for θ is calculated outside the model, which then enters a generalized linear model as a constant (Hilbe, 2011: 10). The relationship between the dependent variable and the independent variables can be expressed as follows (ibid.: 310):

$$ln(y) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p$$

Consequently, the expected value of the independent variable can be calculated by exponentiation (ibid.):

$$y = e^{\alpha} e^{\beta_1 x_1} \cdot \ldots \cdot e^{\beta_p x_p}$$

Where β_i is the estimated parameter for variable i. Additionally, we calculated incidence rate ratios through exponentiation of individual parameters: $e^{\beta_i} = IRR_i$ (Hilbe, 2011: 109f.). To allow comparisons between coefficients for different variables, standardized beta-coefficients are calculated as well. For this, all independent variables are transformed to have a mean value of 0 and a variance of 1. The significance of each variable is assessed by applying Wald tests (Wollschläger, 2014: 295).

To avoid multicollinearity, bivariate correlation analyses were executed between all independent variables and the target variables, using Spearman's ρ. For each pair of variables with higher correlation (|ρ| > 0.5), one variable is removed from the analysis, based on level of detail and correlation to the number of bike-sharing trips. This refers to the FNP usage category 'green spaces' and several sociodemographic variables. Multicollinearity in the final model can be checked using variance inflation factors (VIF) which are usually not accepted when they exceed VIF>10 (Schendera, 2008: 105). Our values do not raise much concern, as they do not exceed

VIF=3 except for 'station with substitute lines' (VIF=3.23) and the FNP categories 'residential building land' (VIF=4.49) and 'special residential building land' (VIF=3.52) which are moderately correlated.

In the first model analyzing spatial relationships, the number of potential influence factors is very large. Therefore, the ones minimizing the Akaike Information Criterion (AIC) value are selected using forward stepwise selection. This can be carried out by applying the function step from the package stats in R. In the second regression, which analyzed the effects of temporal factors, all variables are included in the final model.

3.4 Variables

In the regression models, the number of bike-sharing trips that started within 100x100 m or within one hour was used as the dependent variable. As most starting points also represent the end point of a different trip, the spatial correlation between both distributions is extremely high which allowed us to use both types interchangeably. The starting points are used for ease of interpretation.

3.4.1 Spatial variables

Explanatory variables are mainly selected based on the results of previous research, as described in Section 2.2. Land use data is obtained from the municipal land use plan of Cologne (FNP – Flächennutzungsplan), which defines the planning objectives for the whole city. To calculate the share of green spaces in a grid cell, we used the municipal register of green spaces instead as this provides more detailed information. Topography is excluded from the analysis due to lack of variation.

As previous studies recognize that the impact of POIs differs depending on the type, we distinguish between 12 types of POI (see Table 1). Because the three categories shops, food outlets and bars are highly correlated, they are collapsed into one category. The POI number for each grid cell is calculated as a moving sum of POIs within 3x3 grid cells. There are two reasons for this. First, due to restrictions imposed by the city and nextbike, it is often not possible to park a bicycle directly next to the desired destination, but only in its vicinity. Second, this approach allows us to include the effect of nearby POIs. Similar approaches are applied by Sun et al. (2017), Tran and Ovtracht (2018), Zhao et al. (2019) (POI within a 300 m radius) and Wang et al. (2015) (1/8 mile radius) or Wang and Chen (2020) (500 m radius), usually around bike-sharing docks. In Cologne, bike-sharing is connected to universities through the special tariff for students. Due to their larger size, proximity to universities is calculated differently: i.e. by using the distance from each cell to the closest university building.

To evaluate the relationship between bike-sharing and public transit, distances from grid cells to the closest bus and light rail stations are calculated. Additionally, the light rail stations that were affected by the construction work are separated into four categories that are analyzed in greater detail. Stations can be included in more than one category.

- Closed: at least one line was canceled at this station (some stations were closed completely)
- Diversion: at least one line additionally stopped at this station as part of a detour
- Substitution: the replacement service stopped at this station
- Last: last station at which a line followed its normal route

To analyze whether bicycles are positioned next to large streets and intersections, the distance to the closest arterial road is included as well.

Table 1: Descriptive statistics of independent variables used in the spatial regression

	Description	Min	Max	Mean	Standard deviation
Dependent variable					
Number of trips	Number of bike-sharing trips starting within a 100x100 m grid cell	0	329	8.5248	18.0107
FNP (local land use plan)					
0: Residential building land	Percentage of grid cell used for the relevant land use as defined in the land use plan	0	1	0.2874	0.4030
1: Special residential building land		0	1	0.0911	0.2554
2: Mixed building land		0	1	0.0503	0.1836
3: Commercial land		0	1	0.0875	0.2506
4: Industrial land		0	1	0.0238	0.1390
11: Land for community facilities		0	1	0.0264	0.1163
12: Railway land		0	1	0.0521	0.1787
13: Land for trains		0	0.9910	0.0509	0.1195
15: Core area		0	1	0.0060	0.0603
16: Mixed area		0	1	0.0105	0.0808
17: Special building land		0	1	0.0411	0.1732
21: Redevelopment area		0	0.9732	0.0007	0.0212
Other land use					
Green spaces	Share of grid cell used for green spaces	0	1	0.1610	0.3037
Points of interest					
Sum of shops, food outlets, bars	Number of POIs within 3x3 cells around each grid cell (300x300 m)	0	204	5.5480	15.1447
Healthcare facilities		0	14	0.1741	0.6677
Kindergartens		0	5	0.3764	0.6806
Museums		0	5	0.0353	0.2650
Public institutions		0	4	0.0171	0.1645
Sports facilities		0	7	0.1129	0.3984
Tourist attractions		0	10	0.2146	0.7705
Places of worship		0	3	0.0392	0.2184
Playgrounds		0	4	0.1462	0.4405
Distances to…					
…University	Distance to the closest object of the corresponding category in m (1,000, if distance > 1,000 m)	0	1,000	775.7856	320.4439
…Bus		0	1,000	240.8542	199.5672
…Light rail		0	1,000	378.2974	277.1408
…Closed light rail stations		0	1,000	909.6728	227.5520
…Light rail stations with redirected lines		0	1,000	906.2432	236.5604
…Stations with substitute lines		0	1,000	939.9905	188.1037
…Last regular stop		0	1,000	945.1110	169.7257
…Major arterial		0	1,000	141.6214	192.4173
Sociodemographics					
Population	Number of persons living within a grid cell	0	581	61.2213	84.2935
Share of persons aged 0-17 yrs	Share of persons of the respective age group living within 3x3 grid cells (300x300 m)	0	1	0.1000	0.0911
Share of persons aged 18-29 yrs		0	1	0.2579	0.1176
Share of persons aged 30-49 yrs		0	1	0.1239	0.1860
Share of persons aged 50-64 yrs		0	1	0.1302	0.1039

Several demographic characteristics are included in the model, using data from the 2011 census. These are available on a spatial resolution of 100x100 m grid cells covering the whole area of Germany. The same steps to summarize 3x3 raster cells are applied that are used for POI. In two cells, a share of persons aged 0-17 years occurs. These values are attributable to the data source and do not distort the statistics. We ran the regression without the affected cells to check that it generates practically identical results. Descriptives for all spatial explanatory variables are given in Table 1.

3.4.2 Temporal variables

There are two types of temporal variables used. Dummy variables indicate weekday and time of day. We divide days into time segments that are logically related and show similarly high numbers of trips (see Figure 2). Working days are summarized due to their comparable distribution of use, while separate periods are defined for Saturday and Sunday.

Table 2: Descriptive statistics of independent variables used in the temporal regression

	Description	Min	Max	Mean	Standard deviation
Dependent variable					
Number of trips	Number of bike-sharing trips within one hour	0	316	91.39	66.8274
Weather					
Cloud coverage	Share of sky covered with clouds (in eighths)	0	8	6.0535	2.2956
Air temperature	Air temperature at 2 m above ground in °C	-2.1	24.5	11.8766	4.2504
Precipitation	Hourly precipitation level in mm	0	4.1	0.1426	0.4599
Sun	Hourly duration of sunshine in mins (only between 3:00 and 20:00)	0	60	5.6338	14.7575
	Description		**Percentage**		**Sample Size**
Weekdays					
Monday			14.39%		121
Tuesday			14.27%		120
Wednesday	Dummy variable indicating weekday		14.27%		120
Thursday			14.27%		120
Friday			14.27%		120
Saturday			14.27%		120
Time of day					
Morning	10:00-10:59 on working days, 8:00-11:59 on Saturdays, 7:00-11:59 on Sundays		8.44%		71
Rush Hour (am)	7:00-9:59 only on working days		8.92%		75
Noon	11:00-12:50 on working days 12:00-14:59 on Saturdays and Sundays		9.51%		80
Afternoon	13:00-15:59 on working days 15:00-18:59 on Saturdays and Sundays		13.67%		115
Rush Hour (pm)	16:00-18:00 only on working days		8.92%		75
Evening	19:00-23:00 on all days		13.08%		175
Other time periods					
Semester	Starting on October 7th		81.21%		683
Construction site	October 13th 20:00 – October 28th 03:00		40.90%		344

To evaluate the influence of the construction site, a dummy variable indicates whether an observation originates from the corresponding time. Additionally, the impact of the university is expected to differ after the semester starts. This is after the first week of the observation period.

Furthermore, weather data is included in the analysis. Hourly measurements of the station 2667 Cologne-Bonn are investigated. This station is located at Cologne Airport on the south-eastern edge of the urban area. In a preliminary analysis, wind speed was examined as well. In contrast to previous studies, this variable exhibited only a minor (and, surprisingly, positive) correlation with the number of trips (ρ = 0.1226) and was therefore excluded (Gebhart and Noland, 2014). All temporal variables are presented in Table 2.

4 Results

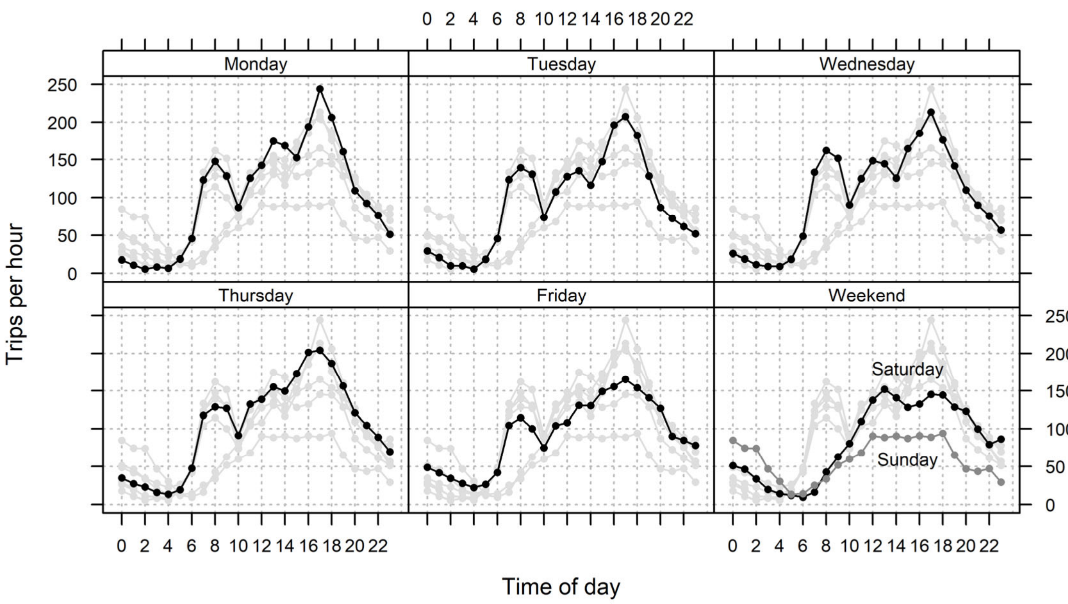
4.1 Usage characteristics

A total of 76,859 trips was counted for all 1,110 bikes in the system over 5 weeks (35 days). Hence, each bicycle was used 69.24 times on average, amounting to 1.98 times per day. Each bicycle was moved at least once within the observation period.

The mean trip distance is measured as a straight line from the origin to the destination and amounts to 1,740.1 m. This is similar to the officially stated mean distance of 1.6 km and verifies the reliability of the data (Anemüller, 2017). Of course, straight-line measurement produces minimum estimates that can offer only a rough indication of actual trip lengths.

Figure 2 shows the aggregated number of trips that started during one hour per weekday over the entire observation period. The BSS is used least during the night, but the number of nightly trips increases through the week, starting Monday. There are peaks between 7:00-9:59, 13:00-13:59 and 17:00-17:59, the last of which represents the daily maximum use. Usage on Saturdays is comparable to that on working days but lacks the first peak. Usage on Sundays differs strongly and shows relatively high trip numbers during the night and low trip numbers during the day, with less variation.

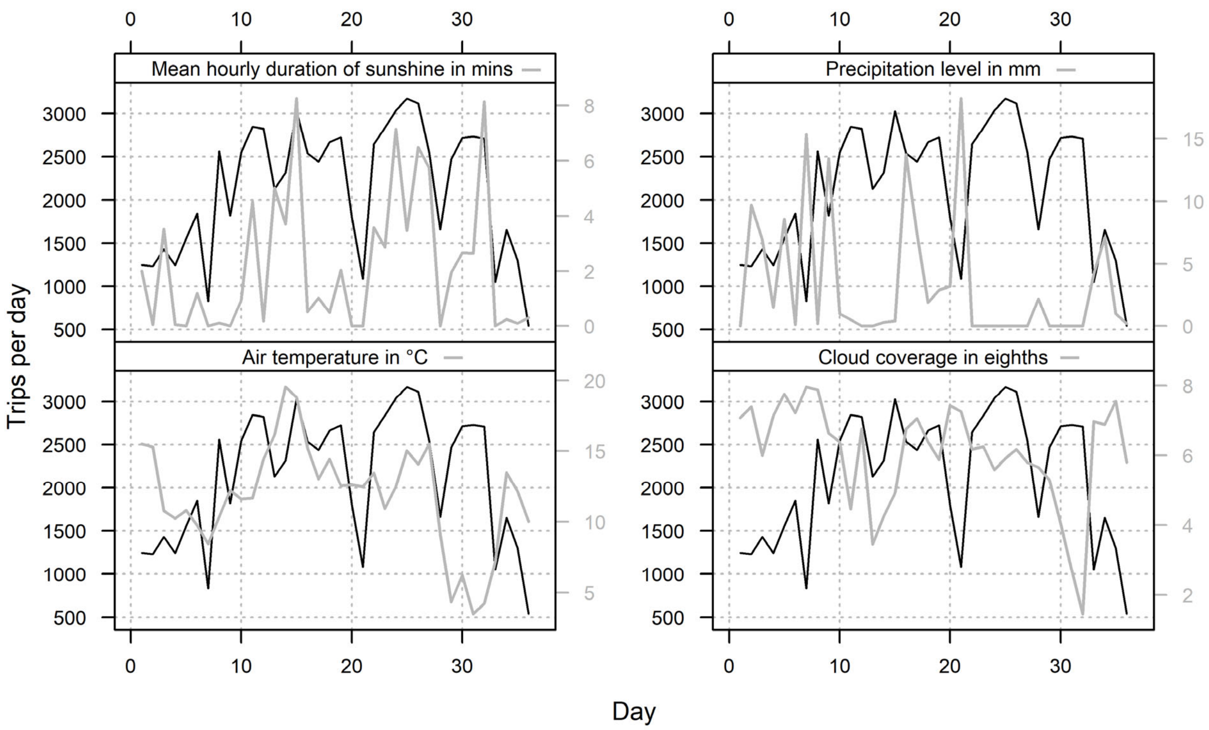
Figure 2: Average trips per hour



Data: Stadt Köln (2020)

Figure 3 shows the daily number of trips related to different weather characteristics. The reoccurring days with distinctly low demand are Sundays. Sunshine and higher temperatures are positively correlated to the number of trips, precipitation and cloud coverage are negatively correlated. But all these correlations are rather weak. The negative correlation between the number of trips and precipitation is most apparent.

Figure 3: Trips per day in combination with weather variables



Data: Stadt Köln (2020); DWD (2020)

4.2 Bike-sharing and public transit

The possibility of continuing a public transit trip using bike-sharing depends mainly on the availability of bicycles at train and bus stops. For each station, we investigate the percentage of times when at least one bicycle was available within a certain radius around the station. Other studies frequently employ a radius of ¼ mile (402.3 m) around railway stations for similar questions (Gebhart and Noland, 2014; Kaviti et al., 2020). In this study, a slightly smaller radius of 300 m is chosen due to the shorter distance between light rail stations in the city center. Within a radius of 300 m around public transit stations at least one bicycle was available in about 50.9% (light rail) and 30.6% (bus), respectively, of all cases. This means that the probability of finding a bike at a light rail station is considerably higher.

As another basic indicator of the relationship between public transit and the BSS, we calculate the number of trips leading to public transit stops. Here, the stops affected by the construction site are examined in separate groups and trips ending within 300 m of stations are summarized. The results are shown in Table 3. Since there is some overlap between the categories, only a few stops are presented as examples. The percentages refer to the total number of trips made in the corresponding period. The locations of the selected light rail stations in the context of the flexzone and the disruptions caused by the construction site are represented in Figure 4.

The average number of total trips per day increases during construction and decreases again afterwards, roughly to the original level. At (semi-)closed stations, the same pattern can be observed, while the percentage of trips attracted by these stations is especially high during construction. Stops with additional redirected lines attract a lower percentage of all bike loans during the construction work but still slightly higher numbers per day. Stops with substitute lines and last stops on the regular route also show slightly higher trip numbers during the construction period, but no clear picture in terms of the percentage of bike loans they attract.

Table 3: Number of trips per day leading to destinations within 300 m of stations that were affected by the construction site

	Before	Before (%)	During	During (%)	After	After (%)
(Semi-)closed stops						
Appellhofplatz	13.0	0.74	19.9	0.9	13.4	0.73
Neumarkt	21.7	1.24	32.2	1.45	24.4	1.33
Poststr.	5.9	0.34	8.9	0.4	5.5	0.3
Severinstr.	12.3	0.7	18.0	0.81	11.5	0.62
Stops with additional redirected lines						
Hansaring	12.1	0.69	13.8	0.62	11.7	0.64
Friesenplatz	19.7	1.13	24.0	1.08	21.7	1.18
Rudolfplatz	22.5	1.28	27.1	1.22	22.8	1.24
Zülpicher Platz	16.4	0.94	19.2	0.86	18.5	1.01
Last stop on the regular route						
Barbarossaplatz	13.1	0.75	16.1	0.72	12.8	0.7
Ebertplatz	17.0	0.97	20.3	0.91	17.6	0.96
Stop with substitute lines						
Suevenstr.	7.0	0.4	7.3	0.33	7.4	0.4
Buchforst, Waldecker Str.	12.3	0.7	14.8	0.67	9.8	0.53
All light rail stations	1052.9	60.05	1362.9	61.40	1099.4	59.90
All trips	1753.3	100	2226.6	100	1835.3	100

Data: Stadt Köln (2020)

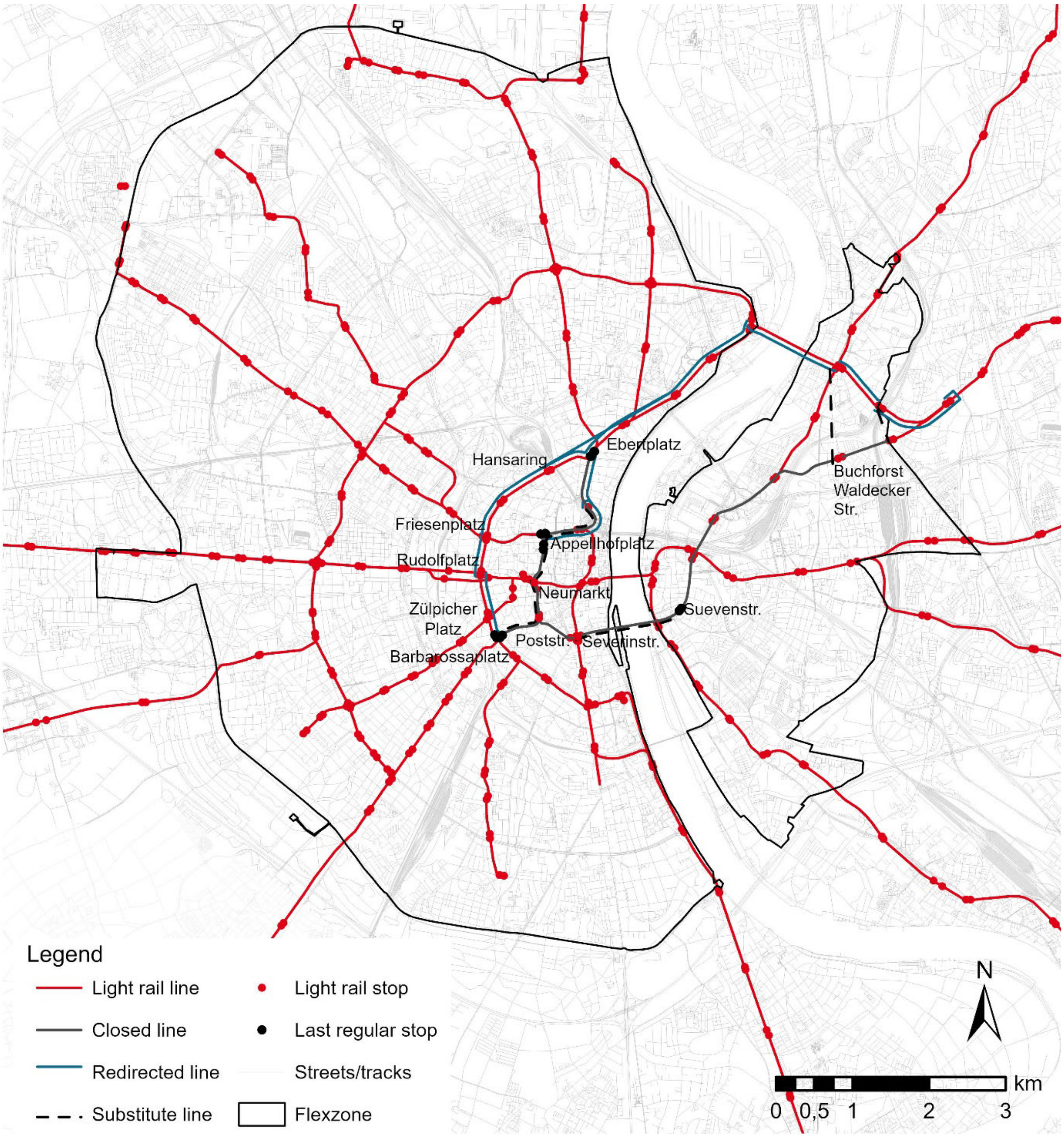
4.3 Model results

In Table 4, the results of the negative binomial regression regarding spatial variables are displayed.

4.3.1 General elements of the urban structure

Most types of land use as defined in the FNP have a significantly positive influence on bike share usage, while three categories were removed from the model. A higher share of green spaces is associated with a lower number of trips. Regarding points of interest, the combined number of shops, food outlets and bars displays a strongly and significantly positive influence. This is in accordance with previous studies. Most other types of POI have a significantly positive impact on bike-sharing usage too, including healthcare facilities, kindergartens, sports facilities, tourist attractions, and playgrounds. Tourist attractions and kindergartens show particularly strong beta coefficients. The influence of museums and churches is marginally significant and four categories were excluded. Proximity to universities is strongly associated with more bike-sharing trips.

Figure 4: Light rail lines including disruptions caused by the construction site



Data: Stadt Köln (2020), KVB (2019); OpenStreetmap

4.3.2 Elements of the transport system

Similar relationships could be discovered for almost all elements of the transport system. In general, the number of bike trips decreases with increasing distance to public transit stations and major arterials, and increases in their proximity. The effects of rail stops impacted by the construction work need to be interpreted in conjunction with the main effect of light rail. E.g., the effect of distance to a closed light rail station is the sum of light rail and closed light rail (β=-0.2389-0,1116 = 0.3505). The variable 'last regular stop' is excluded. Negative coefficients are determined for the distance to closed stops and stops with detours, suggesting that the distance slope near these stations is steeper than that of light rail in general. Conversely, the coefficient for the distance to substitute stops is positive. (Semi-)closed stops show the highest negative beta coefficient among these variables, indicating that additional trips are generated in proximity to

Table 4: Results of the spatial regression

	Coeff.	IRR	Std. Error	β	z-value	p-value
Intercept	1.8328	6.2512	0.1353	1.46060	13.5490	<0.001
FNP						
0: Residential building land	0.6955	2.0047	0.0782	0.2803	8.8980	<0.001
1: Special residential building land	0.5944	1.8120	0.1041	0.1518	5.7130	<0.001
2: Mixed building land	0.9805	2.6658	0.1090	0.1800	8.9990	<0.001
3: Commercial land	0.9987	2.7148	0.0862	0.2503	11.5820	<0.001
4: Industrial land	0.9646	2.6237	0.1243	0.1341	7.7620	<0.001
11: Land for community facilities	0.2182	1.2439	0.1442	0.0254	1.5130	0.1302
12: Railway land	-0.1154	0.8910	0.1138	-0.0206	-1.0140	0.3106
13: Land for trains	1.0281	2.7957	0.1526	0.1228	6.7360	<0.001
15: Core area	1.5910	4.9086	0.2462	0.0959	6.4620	<0.001
16: Mixed area	0.7829	2.1878	0.1910	0.0633	4.0980	<0.001
17: Special building land	1.3528	3.8681	0.1053	0.2343	12.8450	<0.001
21: Redevelopment area	2.9930	19.9462	0.6605	0.0635	4.5310	<0.001
Other land use						
Green spaces	-0.7858	0.4557	0.0873	-0.2386	-9.0060	<0.001
Points of interest						
Sum of shops, food outlets, bars	0.0079	1.0080	0.0013	0.1202	6.0580	<0.001
Healthcare facilities	0.0790	1.0822	0.0233	0.0528	3.3930	<0.001
Kindergartens	0.1627	1.1767	0.0233	0.1108	6.9800	<0.001
Museums	-0.1420	0.8676	0.0650	-0.0376	-2.1860	0.0288
Public institutions	0.1405	1.1509	0.0935	0.0231	1.5030	0.1329
Sports facilities	0.1867	1.2053	0.0374	0.0744	4.9880	<0.001
Tourist attractions	0.2617	1.2992	0.0214	0.2017	12.2160	<0.001
Places of worship (churches)	0.1568	1.1698	0.0682	0.0343	2.2980	0.0216
Playgrounds	0.1462	1.1575	0.0340	0.0644	4.3040	<0.001
Distances to…						
…University	-0.0009	0.9991	0.0001	-0.3027	-16.8590	<0.001
…Bus	-0.0006	0.9994	0.0001	-0.1184	-6.7370	<0.001
…Light rail	-0.0009	0.9991	0.0001	-0.2389	-12.6400	<0.001
…Closed light rail stations	-0.0005	0.9995	0.0001	-0.1116	-5.0040	<0.001
…Light rail stations with redirected lines	-0.0002	0.9998	0.0001	-0.0418	-2.3390	0.0194
…Stations with substitute lines	0.0005	1.0005	0.0001	0.0905	3.5580	<0.001
…Major arterial	-0.0012	0.9988	0.0001	-0.2235	-10.6180	<0.001
Sociodemographics						
Population	0.0034	1.0034	0.0003	0.2865	13.4770	<0.001
Share of persons aged 18-29 years	1.2770	3.5858	0.1565	0.1502	8.1570	<0.001
Share of persons aged 30-49 years	0.3800	1.4623	0.1048	0.0707	3.6270	<0.001
Share of persons aged 50-64 years	0.3384	1.4027	0.1770	0.0352	1.9120	0.0559

these stations. This is in line with the results from the descriptive analysis in Section 4.2. The beta coefficient of stations with additional lines due to detours is rather low. Therefore, only very few additional trips (about 1-4 per day, Table 3) lead to these stations. The positive coefficient calculated for substitute stops underlines that there are even fewer trips in the vicinity of these stations.

4.3.3 Sociodemographic characteristics

A significant influence can be recognized for several sociodemographic characteristics. As expected, the number of bike-sharing trips is positively associated with population density. Additionally, usage seems to vary by age composition in the grid cells, as especially higher shares of persons aged 18-29 have a positive influence on the number of trips. The age group below 18 was excluded from the model. Sociodemographic effects need to be interpreted with great care, though. The associations we study are on the aggregate level of population structures. This means that we face the risk of ecological fallacy. Hence, we cannot directly determine whether any specific population group uses the BSS more often or less often than any other.

Table 5: Results of the time-related regression

	Coeff.	IRR	Std. Error	β	z-value	p-value
Intercept	3.1323	22.9276	0.1334	4.3514	23.4740	<0.001
Weather						
Cloud coverage	-0.0123	0.9877	0.0123	-0.0283	-1.0040	0.3156
Air temperature	0.0278	1.0282	0.0068	0.1180	4.0930	<0.001
Precipitation	-0.2611	0.7702	0.0552	-0.1201	-4.7290	<0.001
Sun	0.0028	1.0028	0.0020	0.0415	1.4150	0.1570
Weekdays						
Monday	0.1850	1.2032	0.0929	0.0650	1.9910	0.0465
Tuesday	0.1938	1.2138	0.0910	0.0678	2.1280	0.0333
Wednesday	0.2644	1.3026	0.0934	0.0925	2.8310	0.0046
Thursday	0.2771	1.3193	0.0937	0.0970	2.9580	0.0031
Friday	0.2501	1.2842	0.0920	0.0875	2.7190	0.0066
Saturday	0.2380	1.2687	0.0896	0.0833	2.6570	0.0079
Time of day						
Morning	0.2921	1.3393	0.0964	0.0813	3.0290	0.0025
Rush Hour (am)	0.9320	2.5396	0.0908	0.2658	10.2590	<0.001
Noon	0.8344	2.3034	0.0925	0.2449	9.0200	<0.001
Afternoon	0.9233	2.5176	0.0807	0.3174	11.4460	<0.001
Rush Hour (pm)	1.3241	3.7587	0.0898	0.3776	14.7450	<0.001
Evening	0.4260	1.5311	0.0759	0.1437	5.6150	<0.001
Other time periods						
Semester	0.3519	1.4218	0.0694	0.1375	5.0700	<0.001
Construction site	0.0271	1.0275	0.0565	0.0134	0.4810	0.6307

Table 5 shows the results of the regression considering time-related variables. In comparison to Sunday, which is used as a reference, all weekdays display a positive influence on the number of trips. Nevertheless, beta values are rather low. This is different for the times of day. All categories show a significantly positive impact and high beta values relative to the reference category 'night'. The greatest positive impact seems to be associated with the morning and evening rush hours, as well as noon and afternoon. The beginning of the semester has a positive influence on bike share usage, which mirrors the effect of proximity to a university as discovered in the spatial regression analysis. In contrast, the period of construction work is not associated with a significant difference in bike share usage. The relationship is positive but very weak. Among the weather variables, air temperature and the amount of precipitation are significant. While an increase in air temperature has a positive impact on the number of trips, the association with precipitation levels is negative.

5 Conclusions

This study offers insights into the ways in which various spatial and temporal factors affect the use of bike-sharing in an urban context. This is a dynamic research field in which geography and especially this journal play an important role. Special attention is paid to the interdependencies of a public transit disruption and bike-sharing. A large construction site causing the closure and re-routing of several important light rail lines in the inner city of Cologne allowed us to analyze changes in bike-sharing use presumably caused by these disruptions.

This study differs from many others by analyzing a free-floating BSS. In Germany, there are very few systems which allow shared bikes to be flexibly dropped off. This kind of data allows us to infer real destinations much better than trip data from dock-based systems. Here, users are free to choose their parking locations, with only minor restrictions. The use of a dock-based system depends to a much greater extent on the prior decisions of the operator determining the locations of docks.

Given the distribution of use and the length of the trips, we can also assume that the tariff system is effective. Many trips seem to be connected with universities or public transit stops and were probably carried out by holders of semester tickets or commuter tickets. The majority of trips are of a length that can realistically be traveled within 30 mins and are therefore free to these user groups. Thus, the fare structure probably has a high regulatory effect, so that desired user groups should be addressed by tariff incentives.

A strong connection between higher education and bike share usage can be found in the regression analysis. Commutes to work seem to account for a large share of the trips as well, indicated by the similarities between the temporal usage structure and commuting patterns that exhibit overlapping peaks. In the regression analysis, we detect positive associations of most land uses with the number of trips. In areas with a high proportion of green spaces, significantly fewer trips can be observed. Bike share usage is also positively correlated with the combined number of shops, food outlets and bars. Other POI that have a significantly positive influence on the number of bike-sharing trips are healthcare facilities, kindergartens, sports facilities, tourist attractions, churches and playgrounds. The number of museums is negatively correlated.

Certain sociodemographic factors are found to impact bike-sharing. In general, population density has a positive influence on the number of trips. Bike share usage also seems to vary by age, as a high share of population aged 18-29 increases the number of trips. This suggests this mode is more attractive to the younger population, but it has to be kept in mind that university students and anyone owning a season pass for public transit are offered free trips up to 30 mins. Furthermore, there is a risk of ecological fallacy when using aggregate data such as ours.

Some spatial association between bike-sharing and public transit can be observed. Proximity to bus and light rail stations as well as to main arterials promotes the use of bike-sharing. The connection of bike-sharing to light rail seems to be stronger than to buses. Additionally, the analysis of light rail stations affected by construction work allows us to draw further conclusions regarding the combination of public transit and bike-sharing. In proximity to stations that were (semi-)closed, the average trip numbers clearly increase during the closure and decrease afterwards. This suggests that trips leading to light rail stations are partly replaced by trips with a rental bike when the regular lines are unavailable. At stops with diversions, where the number of light rail lines increases, thus improving connections and frequency, the number of journeys with the BSS increases only slightly, while the share of these trips decreases. This means that the improvement in light rail service assumedly leads to a shift of trips from bike-sharing to public transit. Again, changes are only temporary, and the share of these trips increases after the construction work. The regression analysis leads to similar conclusions: while calculations show a positive influence for both types of affected stations, proximity to a closed station has a far greater effect on the number of trips. Proximity to a substitute station is even associated with a negative influence on the number of trips. Combined, these results indicate that bike-sharing and public transit can, at least to some degree, substitute for one another. However, the changes in bike-sharing use during construction work are only marginal. Despite the closure of central stops, only a few trips can be identified as shifts from public transit.

It must be noted that a certain percentage of the observed trips are in fact redistribution routes. In addition, trips can only be assigned to the 15-minute periods within which they started and ended, so the exact times cannot be determined. Another problem with this kind of data is that no positions are transmitted during trips. This means that real trip lengths can only be estimated. Although these restrictions are tolerable, as they should not cause the analysis to lead to wrong conclusions, more detailed data could offer even more meaningful insights.

The most important policy conclusion we draw from our results is that the free-floating BSS in Cologne plays a measurable but only weak role as a substitute for public transit. We assume that it rather complements public transit for the last mile as trip destinations are often close to public transit stops. The close spatial connection of bike loans to various POIs, combined with the general observation of the short distances the bicycles are used for, also suggests that the bikes are used to save time on short inner-city trips that would otherwise be undertaken on foot. The increase of trips in proximity to the university and public transit in combination with the short average distance of trips indicates that tariff incentives are effective and a large share of trips is made at no cost for users.

Further research may focus on the potential of BSS to replace driving and, hence, contribute to more sustainable transport, on the potential of BSS to improve the mobility and well-being of those who have no car available, and work with disaggregate data to better determine user and trip characteristics.

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