Ride-pooling in the light of COVID-19

Determining spatiotemporal demand characteristics on the example of MOIA

Journal Article

Author(s):
Zwick, Felix; Fraedrich, Eva; Axhausen, Kay W.

Publication date:
2023-06

Permanent link:
https://doi.org/https://doi.org/10.3929/ethz-b-000573827

Originally published in:
IET Intelligent Transport Systems 17(6), https://doi.org/10.1049/itr2.12293

Received: 1 April 2022 | Revised: 24 August 2022 | Accepted: 26 September 2022

IET Intelligent Transport Systems

DOI: 10.1049/itr2.12293

The Institution of Engineering and Technology WILEY

ORIGINAL RESEARCH

Ride-pooling in the light of COVID-19: Determining spatiotemporal demand characteristics on the example of MOIA

Felix Zwick[1,2] | **Eva Fraedrich**[2] | **Kay W. Axhausen**[1]

[1]Institute for Transport Planning and Systems, ETH Zurich, Zurich, Switzerland

[2]MOIA GmbH, Hamburg, Germany

Correspondence
Felix Zwick, Institute for Transport Planning and Systems, ETH Zurich, Zurich, Switzerland.
Email: felix.zwick@ivt.baug.ethz.ch

Abstract

The mobility provider MOIA operates Europe's largest contiguous electric ride-pooling service in Hamburg, representing a testbed of how shared and digitized transport can help foster the transformation of urban mobility. The on-demand service has been in operation since 2019 and was thus affected by the COVID-19 pandemic in 2020. This study shows real-world insights into travel behavior before and during the pandemic, contributing to the empirical evidence on recent mobility behavior. After the application of descriptive statistical analyses, several (spatial) regression models are estimated to understand the relationship between spatial variables and demand. MOIA trip data from three different time periods are used: (a) before the COVID-19 pandemic in summer and autumn 2019, (b) during the time of the first lockdown in Germany in spring 2020, and (c) after the first lockdown in summer and autumn 2020. A significant positive effect on ride-pooling demand is observed for number of inhabitants, workplaces, gastronomic facilities, and at the airport in all time periods. In the course of the pandemic, the main travel patterns remained stable. However, the positive influences of gastronomy and the airport on ride-pooling demand diminished in 2020. In contrast, the impact of hospitals on ride-pooling demand increased in the course of the pandemic. In areas with high car ownership, ride-pooling demand declined compared to pre-pandemic times.

1 | INTRODUCTION

The city of Hamburg has taken on a pioneering role in the field of intelligent transport systems (ITS), which is reflected not least in the Smart City Index 2020 [1], in which Hamburg holds the top position both in the field of mobility and in the overall ranking. Hamburg's ITS strategy aims to make the transport system more efficient, safer and more sustainable, and to provide citizens with an attractive mobility offer at all times [2].

A relevant pillar within this strategy is digitized on-demand mobility services that complement the city's strong public transport system and offer a flexible and convenient alternative for transport users. Among other digital on-demand solutions like car-, bike-, or scooter-sharing, is ride-pooling, a service which dispatches incoming requests to an available vehicle, and bundles trips with similar routes together. Consequently, the number of vehicle kilometers traveled (VKT) can be reduced compared to when rides are conducted alone (e.g. by car or ride-hailing/taxi) [3, 4]. This way, ride-pooling contributes to a reduction of negative traffic externalities like congestion, greenhouse gas emissions and noise, among others.

The ride-pooling provider MOIA launched its on-demand ride-pooling service in Hamburg in April 2019 and provides up to 500 battery-electric 6-seater vans within a 198 km^2 service area, thus covering large parts of the city. With this fleet size, MOIA operates Europe's by far largest contiguous ride-pooling offering [5]. MOIA vehicles are booked via smartphone application and customers are picked up and dropped off at virtual stops located near their desired origin and destination. Despite MOIA being an on-demand service, a prebooking functionality was launched in 2021, allowing to book a vehicle up to 24 hours in advance. The prebooked trips are still pooled together with on-demand trips. The MOIA service is integrated into the multimodal Mobility-as-a-Service (MaaS) booking platform hvv switch[1] that allows booking of multiple on-demand services and public transportation.

In the beginning of the COVID-19 pandemic in 2020, demand for mobility collapsed abruptly. Ride-pooling services were also no longer in demand, which caused the MOIA service in Hamburg to be paused as of 1/4/2020. In order to offer a convenient and safe alternative to public transportation, MOIA offered a special night service from 1/4/2020 to 24/5/2020 between 12 a.m. and 6 a.m. with 100 vehicles on behalf of the city of Hamburg [6]. During this period, pooling was restricted to a maximum of two travel parties. After this time, MOIA resumed offering normal daytime service. The night service was reintroduced during the second lockdown in Germany in April and May 2021. Since June 2021, MOIA operates its conventional service again.

Due to the small number of large-scale ride-pooling services, especially in Europe, there is little research on ride-pooling in practice yet—be it in relation to usage and users, characteristics for demand, or implications on the overall transport system. However, this evidence is critical to better determine the potential of pooled on-demand services to reduce negative transport externalities. In addition, the evolution of ride-pooling demand over time can provide valuable insights into how new mobility services have faced challenges, particularly in light of the COVID-19 pandemic, which has changed travel behavior and subsequently impacted private and public mobility service providers.

The paper provides a systematic analysis of the spatiotemporal determinants of MOIA's demand before the COVID-19 outbreak, during MOIA's night service in April and May 2020, and between the first and second lockdown in Germany that year. Various spatial factors and their influence on MOIA's demand in three time periods (pre-pandemic, lockdown and pandemic) are identified using spatial regression models. Results from an ordinary least squares (OLS) regression, a Spatial Durbin Error Model (SDEM) and a Geographically Weighted Regression (GWR) model are presented. This allows to determine how demand for ride-pooling evolved over the course of the COVID-19 pandemic until November 2020.

2 | BACKGROUND

Supported by ongoing digitization processes and increasing user needs regarding flexibility and individualization, smartphone-based on-demand mobility services have risen world-wide. Amongst the most popular as well as wide-spread on-demand mobility providers are the Transportation Network Companies (TNCs) Uber and Lyft in the U.S. and DiDi in China, which primarily offer private (unpooled) rides. In some cases, they also offer pooled rides, and there are research studies on the spatial context in which pooled services are used, which are presented in Section 2.1. An overview of the ride-pooling market in Europe and related research is provided in Section 2.2. Finally, an overview of the impact of COVID-19 on the mobility market is given in Section 2.3.

2.1 | Spatial characteristics of ride-pooling demand

Multiple studies investigated the spatial adoption of ride-pooling in comparison with ride-hailing, when both services are offered. The most dominant finding is a higher adoption rate of ride-pooling in areas with lower incomes [7–11] in Chicago, Los Angeles and California. Additional factors for lower ride-pooling usage were found to be airport trips [7], higher age [9–11], and lower population density [10, 12].

Aberle [13] examined the service areas of four ride-pooling systems in Hamburg with regard to how they are able to serve economically deprived groups and found that three out of four services are underrepresented in areas with lower income levels and older populations while the service areas where they operated by the time the study was conducted was also more densely populated. Out of the four services the author considered in his investigation, one operator shut down its service in Hamburg, one has changed its service area, and one does not offer pooled rides anymore, which demonstrates the quickly changing mobility landscape in particular during the COVID-19 pandemic.

Another spatiotemporal analysis of pre-pandemic MOIA demand revealed a significant positive impact of population, workplaces, rail stops, cultural and gastronomical facilities on ride-pooling demand [14]. Using MOIA's service in Hanover as an example, it was shown that the spatial pattern can be well extrapolated to other spatial environments to predict the demand for ride-pooling in new cities.

2.2 | Research on ride-pooling systems in Europe and MOIA

In Europe, ride-hailing operators face strong regulations in order to protect public transport and the taxi market and to avoid potential negative implications on the transport system (e.g. increases in kilometers traveled). Consequently, several operators have risen in recent years that only offer pooled trips. One of the first of these services was Kutsuplus in Helsinki, Finland. Weckström et al. [15] analyzed the service's demand and found the highest concentration of origins and destinations in the inner-city area, respectively, areas with highest population and job density, as well as public transport accessibility. Although the service area spanned across a broader part of the city of Helsinki, trips orbital or transversal to the city center were rare. Knie and Ruhrort [16] found a similar concentration of demand in central areas for the ride-pooling service CleverShuttle in Berlin, Dresden, Munich and Leipzig in Germany. The services in Berlin, Dresden and Munich were shut down during the pandemic.

[1] https://www.hvv-switch.de/en/, last accessed: 31/03/2022

The size of ride-pooling services is often limited to fleet sizes smaller than 50 vehicles [5]. The MOIA service in Hamburg is one of few exceptions and operates with more than 200 vehicles.

The MOIA service was studied extensively in simulation studies [17–20] and user (behavior) research [21, 22]. Gilibert et al. [21] and Kostorz et al. [22] found that leisure activities and airport transfers were among the main travel purposes for MOIA trips. Users were found to be more multimodal than average, using multiple modes of mobility over the course of a week. Looking at these results, it is conceivable that altered mobility behavior subsequent the pandemic has affected ride-pooling demand negatively. Kagerbauer et al. [17] published the most comprehensive report on the current use of MOIA and possible future scenarios under different policies and technological developments regarding autonomous vehicles.

2.3 | COVID-19 and (on-demand) mobility

The COVID-19 pandemic led to a drastic decrease in face-to-face contacts and activities and thus to a radical change in mobility behavior starting in the spring of 2020. Meanwhile, many studies have examined the impact of the pandemic on mobility behavior in general and on on-demand mobility in particular.

A common method to study changing mobility patterns is the analysis of mobile phone data, which is widely available and provides revealed movement observations. Researchers worldwide used mobile data to understand mobility behavior and the effectiveness of measurements [23–27]. The most dominant effect of the pandemic in spring 2020 was a drastic decline of mobility. Molloy et al. [24] observed a reduction in average daily distances of about 60%, with the highest reduction of more than 90% occurring in public transportation, where large groups of people meet that can potentially spread the virus.

Kucharski et al. [28] used a mathematical simulation model to assess the potential for the virus to spread in ride-pooling systems and found that there is a significant risk of causing chains of infection if no action is taken. However, the number of contacts in ride-pooling systems is much lower compared to public transportation. MOIA users of the night service in 2020 reported feeling much safer from infection compared to public transportation trips, likely due to the occupancy restrictions and hygiene measures that were put in place [6].

To learn more about personal preferences, feelings, and travel intentions with regard to COVID-19, surveys were conducted to provide insight into the causal relationships of changing mobility behavior [29–32]. Borkowski et al. [30] surveyed more than 1,000 respondents from Poland, finding that the time people spent for mobility was reduced by over 50% during the first lockdown in their country compared to pre-pandemic times. Important causes were the introduction of working from home possibilities and school students not going to school during the lockdown. Eisenmann et al. [31] and Kolarova et al. [32] surveyed a representative sample of 1,000 people in Germany in April 2020 and found that multimodal mobility behavior and public transportation use was increasingly avoided during the pandemic. At the same time, an increased preference for monomodal car use was reported compared to pre-pandemic times. 25% of the working respondents reported to work at least partially from home [32]. De Haas et al. [29] reported even higher shares (39%) of people working from home in the Netherlands surveying a panel of 2,500 respondents. 27% of them expected to also work more from home in future compared to pre-pandemic times. They also found a lower preference to use public transportation in future, whereas the respondents expected to increase their private car use.

The findings indicate a clear increased preference to use private cars in future as public transport use is perceived less safe than in pre-pandemic times. However, transport network capacities of most cities are not capable of handling an increased amount of private car traffic [33] and instead, many cities aim to decrease private car traffic in future.

The above findings show the need to introduce and expand attractive shared mobility services to provide a safe alternative to public transport without causing as many negative externalities as private car transportation. Ride-pooling is one potential alternative and offers a similar level of comfort as a private car, but uses significantly fewer resources and causes fewer negative externalities [3, 4].

A few studies are available studying the impact of COVID-19 on the use of ride-pooling and ride-hailing services.

Jabbari and Mackenzie [34] asked 277 persons in the U.S. in 2019 and again in May 2020 about their willingness to share rides with strangers. They found no significant change in the general dislike to share rides with strangers but a lower willingness to share rides to save money, indicating a higher willingness to pay for private rides. Gaber and Elsamadicy [35] surveyed 398 Uber users in Egypt and found no reduced acceptance of the service in light of the pandemic and potential fears of infection.

Wang et al. [36] collected trip data of the ride-sharing industry in three major cities of China from September 2019 and August 2020 and analyzed adopted driver behavior during the pandemic. It was found that with increasing numbers of COVID-19-infections, drivers completed fewer trips and earned less although the number of shifts was only slightly reduced. A major difference to the ride-pooling service MOIA is that MOIA drivers are directly employed with the company and earn their wages independently of the number of served trips, which is a substantial insurance for drivers against declining demand. Zhang and Liu [37] found an ambiguous attitude of almost 1,000 survey respondents in China towards adopting ride-pooling due to potential negative health threats and potential positive environmental impacts.

2.4 | Contribution

This research aims to provide a better understanding of the changed demand characteristics of ride-pooling in the course of the COVID-19 pandemic on the example of MOIA in Hamburg. While multiple studies examined the changing mobility behaviour regarding public transportation and private car use, only few studies exist on the consequences on ride-pooling service, particularly in Europe. Furthermore, no studies on the spatial characteristics of ride-pooling demand in the light of the pandemic were found.

The three main contributions of our study are as follows:

- We provide a comprehensive spatial analysis of the relationship between ride-pooling demand and multiple spatial data.
- Spatial characteristics are observed over time and for different service types. In this way, we contribute to the understanding of how ride-pooling services are designed for specific purposes and in light of COVID-19.
- In doing so, we fill a gap in the literature on real-world observations of ride-pooling demand during the pandemic.

3 | DATA INPUT

We investigate the MOIA trips during three different time periods:

a) 651,233 trips from June to November 2019 before the COVID-19 pandemic, and during the ramp-up phase after MOIA's launch in April 2019.
b) 58,595 trips from April to 24 May 2020 during the MOIA night service in the entire city of Hamburg but only from 12 a.m. to 6 a.m.
c) 615,560 trips from June to November 2020 in between the first and the second lockdown in Germany.

The ride-pooling service faced a steadily growing demand after its launch in April 2019, which has only been interrupted by the outbreak of COVID-19 and the subsequent collapse in transport demand. During the first lockdown in Germany between March and May 2020, the regular MOIA service was paused and re-started operations by the end of May. However, during this time, the company provided a ride-pooling nighttime-service on behalf of the city with 100 vehicles in the entire city of Hamburg to complement public transport [6].

MOIA's travel demand is evaluated and the ride-pooling trips related to multiple spatial (open) data taken from [38], [39] and the [40]. The data are matched on statistical zones taken from the transport model, which are shown in Figure 1.

The city of Hamburg covers roughly 750 km^2 and is divided into 1,177 statistical zones with smaller zones in the city center and in densely populated areas, and with larger zones in rural areas. A characteristic spatial element of Hamburg is the river Elbe, which divides the city into northern and southern parts and can only be crossed via two tunnels (one for motorized vehicles, one for cyclists and pedestrians only), the Elbe bridges or one of several ferry lines. While Hamburg's central station is located next to the city center, the airport lies in the north-western part of the city.

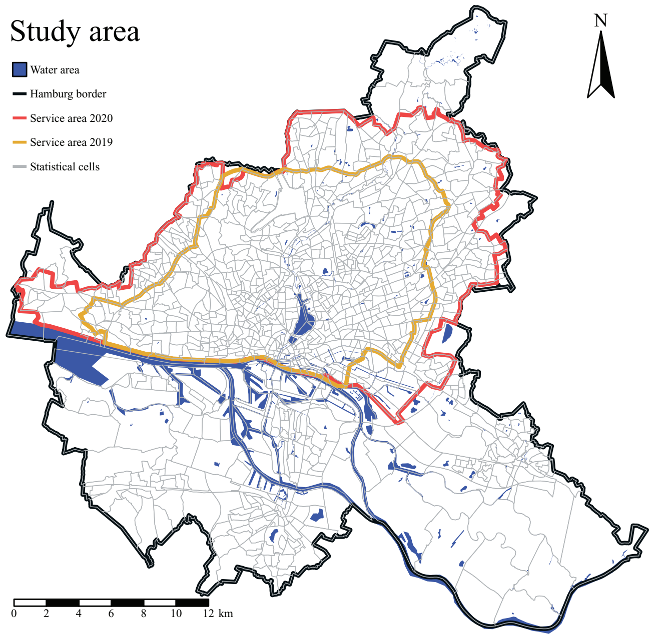

FIGURE 1 Study area with the three considered service areas and statistical zones in Hamburg, Germany

The MOIA service has been operating in different service areas since its launch in April 2019 (see Figure 1). In 2019, the service area covered almost 200 km^2 (yellow line in Figure 1) of the city, already making it one of the largest ride-pooling service areas in Europe. In 2020, the service area was enlarged to cover more than 300 km^2 (red line in Figure 1). During the first lockdown in Germany in light of the COVID-19 pandemic, MOIA operated its night service on behalf of the city of Hamburg in the entire municipal area (750 km^2). The methodology presented in Section 4 allows for the analysis and comparison of all three services. It should be noted, however, that in addition to the pandemic itself, the change in service areas and service times also influence the results.

3.1 | Trip data

Figure 2 shows the temporal distribution of the ride-pooling trips in each time period. The number of trips per month and per day of the week during the night service was substantially lower than during MOIA's conventional service. This is hardly surprising given that the provider operated only with 100 vehicles during that period, the operating hours were restricted to the night-time, and strict curfew rules were in place during this lockdown period.

The number of trips per month increased from June to October in 2019 and 2020 and were almost at the same level which reflects the ramp-up of the MOIA fleet and a similar demand development in both years. However, in November 2020 the number of trips decreased, presumably due to increasing numbers of COVID-19 infections, and thus a decreased travel demand. In 2019 in contrast, the number of trips continued to increase in November, a trend that was only stopped

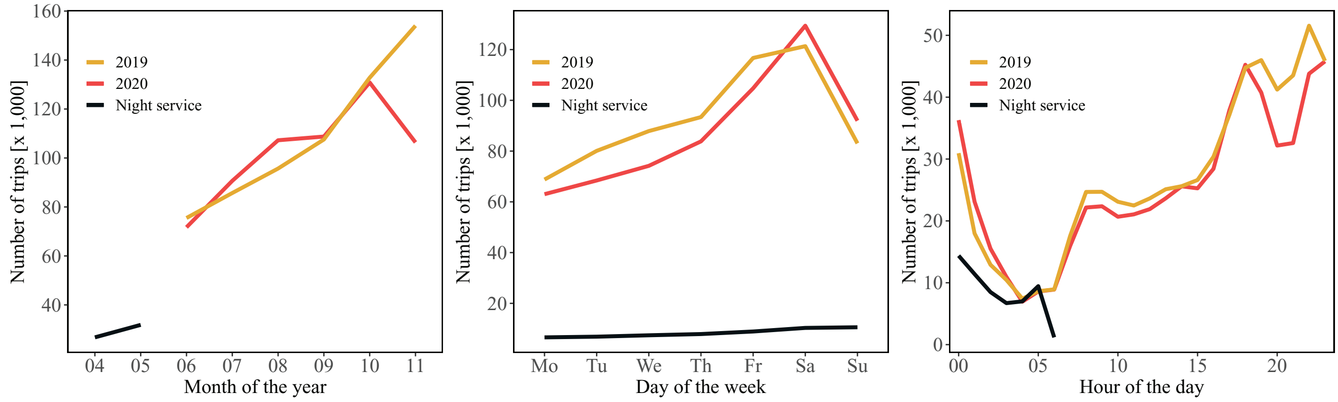

FIGURE 2 Temporal distribution of MOIA trips

by COVID-19 in spring 2020. The number of trips during the course of a week are similarly distributed in 2019 and 2020, although slightly more trips were done on Saturdays and Sundays in 2020 than in 2019.

Looking at the hourly trip distribution, a demand peak can be observed during evening and night-times from 6 p.m. to 12 a.m. The distribution over the two years is similar. In 2020 however, less trips occurred between 7 p.m. and 11 p.m., which is assumed to be a consequence of rigorously reduced leisure activities when bars, restaurants, movie theatres, night clubs, and similar venues were closed completely, or had only limited opening hours and capacities.

The share of actually pooled trips, that is, trips with at least one other booking inside the vehicle for at least a part of the trip, was 56% in 2019, 54% during the night service and 63% in 2020. Pooling was restricted to two parties during the night service. The share of pooled trips increased during the pandemic, which is more likely the result of an improved dispatching algorithm than a change in passenger behavior. Surveyed customers of the night service reported that they feel much safer in a MOIA vehicle compared to public transportation [6].

Figure 3 shows the spatial distribution of origins and destinations of MOIA trips in the three considered time periods in the respective service areas.

Similar spatial patterns for all three services can be observed. The highest trip density is observed around the lake Alster in the central areas of Hamburg. Another demand hotspot in 2019 was the airport in the northern part of the city (largest cell displaying two runways). During the night service and in 2020, the airport was frequented less by MOIA. Large park areas in the western part (Altonaer Volkspark), north-western part (Niendorfer Gehege) and north-eastern part (Ohlsdorfer Friedhof) of the city do not attract high-demand densities during all time periods as there are less streets and only few departure or destination stops on very large areas. Although the service area covered all of Hamburg during the time of the night service, most of the trips (86%) still took place within the 2020 service area [6], followed by the southern regions of Wilhelmsburg and Harburg, and the south-eastern region of Bergedorf.

3.2 | Spatial data

The following explanatory variables are used sorted by sources:
Transport Model of the City of Hamburg [40] (2018):

- Number of inhabitants per statistical zone.
- Number of workplaces per statistical zone.
- Cars per inhabitant per zone calculated as the number of private cars registered in a zone divided by the number of inhabitants in the respective zone.

Transparenzportal Hamburg [39] (2020):

- Hospitals in Hamburg including number of beds in each hospital to consider the hospital size.
- Social status of each statistical zone. This categorical variable is calculated yearly by the city of Hamburg considering the following seven indicators [41] (2019):
  - Share of children below 18 years with migration background.
  - Share of children below 18 years with a single parent.
  - Share of population receiving social support due to unemployment or asylum.
  - Share of unemployed population.
  - Share of children with minimum income.
  - Share of people older than 65 with minimum income.
  - Share of graduation types.

OpenStreetMap [38] (2020):

- Gastronomic facilities: Amenities of category bar, biergarten, café, fast_food, food_court, ice_cream, pub and restaurant.
- Shopping facilities: Shops of category supermarket, mall, general, department_store, clothes and furniture.
- Rail stops: Rail stations weighted with the number of platforms to consider the station size. All types of rail-based transport modes are considered.

Additionally, the four long-distance railways stations *Hauptbahnhof* (main station), *Dammtor*, *Altona*, and *Harburg* and the airport

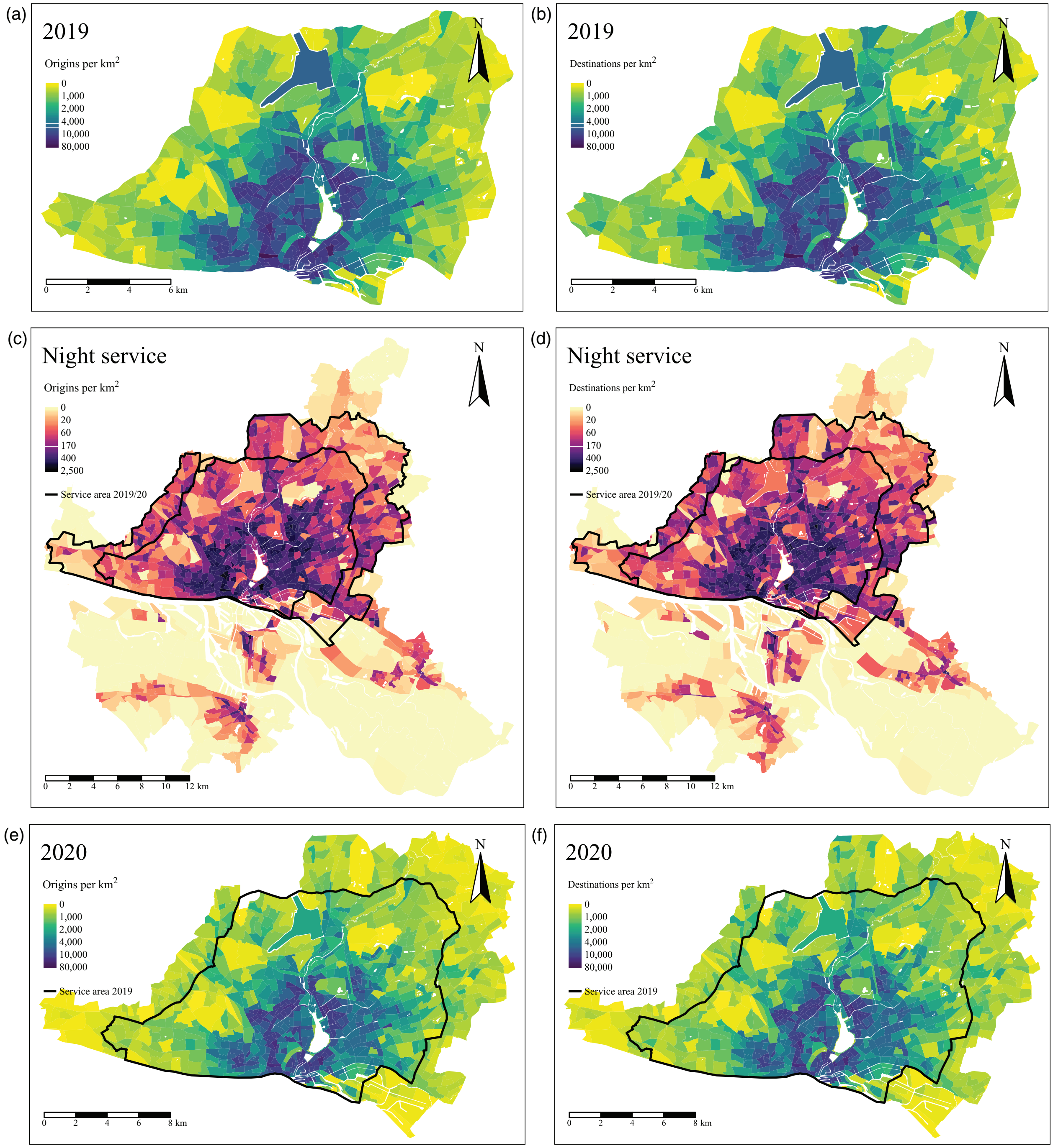

FIGURE 3 Spatial distribution of origins (left) and destinations (right) per km^2 for the three considered services. The lake Alster in the city center is displayed in white.

are taken into account. The airport is located in the north-west of Hamburg roughly 10 km from the city center. Table 1 shows the quartiles of occurrence of each independent variable in the statistical zones, which indicates the variables' distributions.

Figure 4 shows a colored correlation matrix for the independent variables. A correlation above 0.5 is observed between the variables *rail stops* and *long-distance station* and between *gastronomy* and *shopping*. This is not surprising as rail stops at long-distance stations are also considered. Gastronomic facilities are often located close to shopping facilities. Correlations are within an acceptable range but must be considered in further investigations.

More independent variables like *age*, *number of employed people*, or *number of university students* were investigated but excluded due to high correlation with other variables or insignificant estimation results.

TABLE 1 Quartiles of occurrence of independent variables in the statistical zones of the city of Hamburg

	Min	1st Quartile	Median	Mean	3rd Quartile	Max
Inhabitants [x1000]	0	0.60	1.68	1.63	2.44	6.10
Workplaces [x1000]	0	0.12	0.31	1.08	1.00	17.97
Hospital beds [x1000]	0	0	0	0.01	0	1.76
Rail stops	0	0	0	0.30	0	18
Gastronomy	0	0	2	3.91	4	99
Shopping	0	0	0	1.39	1	85
Cars per inhabitant	0	0.24	0.32	0.31	0.41	0.90
Social status	83 zones very low; 89 zones low; 662 zones medium; 172 zones high; 171 zones missing (e.g. as uninhabited harbor zones)					

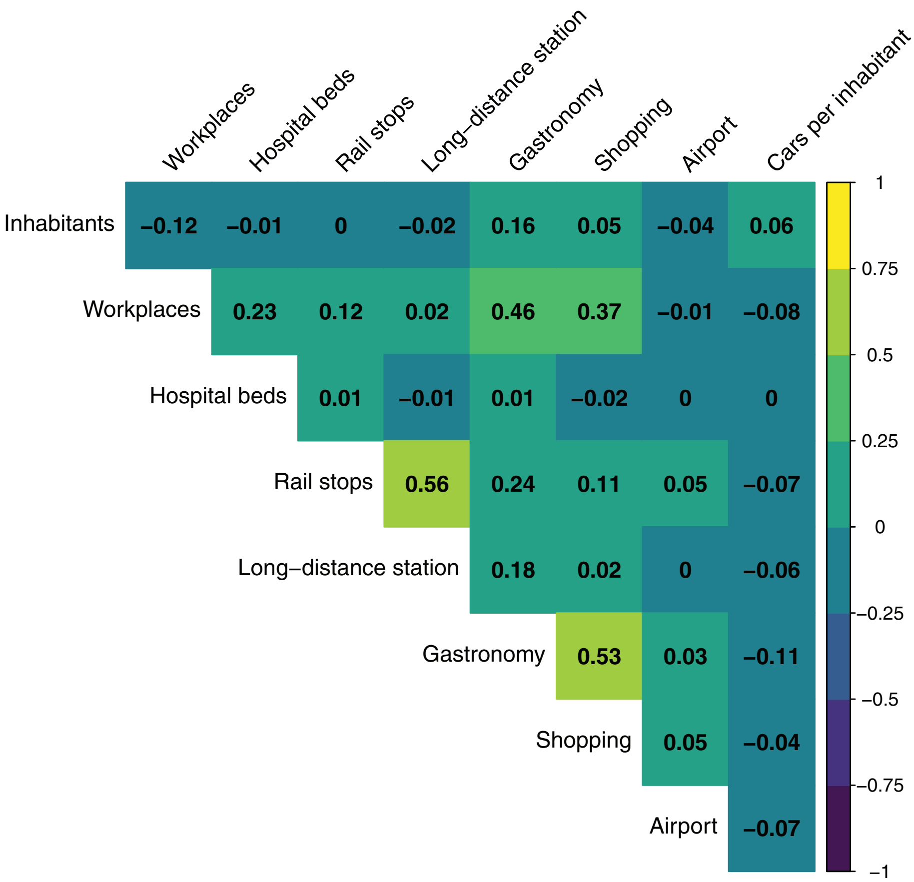

FIGURE 4 Correlation matrix of independent variables

4 | METHODOLOGY

All data are matched to the 1,177 statistical zones presented in Figure 1 that define the structure of the estimated models. The number of zones is reduced according to the considered service areas (875 zones within the 2020 service area, 650 zones within the 2019 service area). To define the number of each variable's occurrences in each zone, the spatial data is matched on the raster based on their geographical coordinates. Three regression models are applied to investigate the influence of the explanatory variables on ride-pooling trips. First, we apply an ordinary least squares (OLS) regression model that is defined by

$$y = X\beta + \epsilon, \tag{1}$$

where y denotes the dependent variable, X denotes the independent variable, β denotes the estimated coefficient and ϵ denotes the error term. The model does not take into account any spatial pattern within the data, which the other two regression models introduced in the remaining section do.

The spatial distribution observed in Figure 3 indicates spatial autocorrelation within the data. To detect this autocorrelation, contiguous zones for each zone are defined using the queen criterion, that is, zones sharing a common border or vertex are defined as contiguous zones. The data was edited such that zones sharing a common border across the river Elbe are not defined as neighbors. We then execute Moran's I [42] and Lagrange Multiplier [43] tests to identify spatial error autocorrelation and to define which spatial model needs to be taken into account. The Moran's I test results are highly significant (p-value < 0.01) for all models, indicating that a spatial regression model is more suitable to explain the given data. The Lagrange-Multiplier tests indicate a spatial lag and a spatial error dependence for all models.

We followed Anselin [44] and LeSage and Pace [45] and investigated a Spatial Error Model (SEM) that incorporates a spatial error term, a Spatially Lagged X Model (SLX) that incorporates a spatial lag from the independent variables and a Spatial Durbin Error Model (SDEM) that combines the SEM and SLX model. A spatial lag of the *independent* variables is incorporated as we assume that the ride-pooling demand within a zone is rather affected by the characteristics (e.g. number of gastronomic or shopping facilities) of a contiguous zone than by the number of ride-pooling trips in a contiguous zone.

Considering the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and likelihood-ratio tests, we find that the SDEM model has the best statistical fit for all six data sets. The SDEM model is defined by

$$y = X\beta + WX\theta + \epsilon,$$
$$\epsilon = \lambda W\epsilon + u, \quad (2)$$

where W denotes the spatial weight matrix, θ denotes the coefficient for local spatial spillovers, ϵ denotes the error term including a spatial component, λ denotes the autoregressive parameter for the error lag and u denotes a non-spatial error term.

Through the model, we can define (1) the direct effect that the independent variables have on the ride-pooling demand within a zone and (2) the indirect spillover effect that the independent variables have on the ride-pooling demand in all contiguous zones.

In addition, a Geographically Weighted Regression (GWR) model is estimated [46, 47]. The model allows to identify spatial non-stationarity in the data and estimates multiple *local* regression models instead of one *global* regression model. The model is defined by

$$y_i = X_i\beta_i + \epsilon_i, \quad (3)$$

where i denotes each location for which a local regression model is estimated.

Each local regression model is estimated taking into account all observations within a previously defined distance, the so-called bandwidth. We use an automated approach defining the bandwidth by minimizing the AIC, which indicates a good model fit. To allow comparison across all six models, we define a single bandwidth for all models by taking the median of all six bandwidths.

Overall, three regression models are estimated. Each model provides additional insights into the spatial demand characteristics over time, supporting the contributions mentioned in Section 2.4. Table 2 lists the main contribution and spatial dimension of each model. The SDEM and GWR model are both based on the OLS regression.

TABLE 2 Main contribution and spatial dimension of each estimated model

Model	Main contribution	Spatial dimension
OLS	Global effects of independent variables on ride-pooling demand	One global model
SDEM	Spatial spillover effects of independent variables; spatial error detection	One global model
GWR	Spatial variance; local anomalies	Multiple local models

5 | RESULTS

In the following, we present and analyze the results of the OLS, the SDEM regression and the GWR model to explain the spatial pattern of MOIA trip origins and destinations for the three considered time periods.

5.1 | Ordinary least square regression

The results of the OLS regression model are given in Table 3.

A high statistical fit is observed for the 2019 and 2020 data with adjusted R^2 values above 0.7. The R^2 values for the night service data are 0.49 and 0.45, which is still reasonable. A significant positive impact of the number of inhabitants, workplaces, gastronomy and the airport is observed throughout almost all models. The positive impact of inhabitants increase in 2020 compared to 2019, while the impact of workplaces decreased.

To investigate the impact of railway services on the ride-pooling demand, two variables are introduced: Rail stops and long-distance stations. While rail stops are weighted with the number of platforms of a train or metro station, long-distance stations are binary—either a station exists or not. We observe a strong positive impact of long-distance stations in 2019 but no significant impact of rail stops, indicating that intermodal trips were mainly made in combination with inter-city travel. During the night service, no significant impact of long-distance stations is observed but a strong significant impact of rail stops. In 2020, significant positive impacts are observed for long-distance stations *and* rail stops of any kind.

The influence of the number of hospital beds varies over time. It only significantly influences trip destinations during the time of the night service and significantly influences origins and destinations in the 2020 data. The reason that hospitals only attracted arriving trips during the night service but not

TABLE 3 OLS regression results

	2019		Night service		2020	
	Origin	**Destination**	**Origin**	**Destination**	**Origin**	**Destination**
Intercept	−68.2	−101.2	18.4***	18.1***	−120.1*	−124.4*
Inhabitants $\frac{1}{1000}$	175.9***	195.7***	21.0***	19.9***	220.7***	225.1***
Workplaces $\frac{1}{1000}$	61.2***	61.2***	2.3***	5.5***	48.6***	55.4***
Hospital beds $\frac{1}{1000}$	327.4	274.2	1.3	83.2***	406.7**	405.1***
Rail stops	31.6	31.8	9.7***	6.7***	42.7***	47.8***
Long-distance station	1,664.4***	1,764.8***	3.4	19.0	1,289.3***	1,347.1***
Gastronomy	86.6***	76.4***	1.6***	0.8***	46.1***	39.9***
Shopping	−19.3***	−19.6***	−0.5*	−1.0***	−6.5**	−5.2*
Airport	28,685.8***	25,099.6***	5.1	145.0***	8,576.6***	8,005.7***
Cars per inhabitant	−565.5**	−484.2**	−43.8***	−37.4***	−661.3***	−599.4***
Social status high	482.4***	507.2***	−9.5*	−7.4	447.8***	435.4***
Social status medium	310.8**	339.4***	4.7	3.4	376.7***	368.2***
Social status low	59.2	134.4	3.4	4.5	161.5**	175.4**
Social status very low	0	0	0	0	0	0
Social status missing	434.2***	453.0***	−12.7**	−9.4*	435.7***	425.4***
Adjusted R^2	0.83	0.81	0.49	0.45	0.71	0.72
AIC	10,292.2	10,243.0	11,764.3	11,725.0	13,050.7	12,896.3
BIC	10,359.4	10,310.1	11,840.4	11,801.0	13,122.4	12,967.9

1Significance indicators: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

departing trips was presumably caused by the restricted service times that only matched well with the start times of hospital shifts but not with the respective end times. This observation was previously discussed in [6]. Apparently, hospitals significantly influence the number of MOIA origins and destinations after the first lockdown, which is likely an effect of the pandemic.

While the number of gastronomic facilities has a significant effect throughout all the models, the impact in the 2020 model is roughly half of the effect of 2019. This clearly indicates a decrease of the positive effect of restaurants and bars on ride-pooling demand—and is barely surprising considering the challenges that gastronomic services were facing in light of the pandemic. Shopping facilities have a negative impact on demand in all periods. The observed correlation with gastronomy (see Figure 4) hints towards a correction of the high positive impact of the gastronomic facilities. A high positive impact on the number of MOIA trips—origins even more than destinations—can be seen for the airport. Hardly surprising, the effect decreases in 2020 when the pandemic caused drastic declines in air travel [48]. During the night service, almost no travel to or from the airport took place at all.

Cars per inhabitant show a significant negative effect on the number of trips throughout all models. The effect even increases in 2020 compared to 2019, which indicates that car owners rely on and use their car even more than before the pandemic. This change in travel behavior was also found by Eisenmann et al. [31] and Kolarova et al. [32].

For the influence of the categorical variable social status, the lowest category (very low) functions as the base alternative. While we observe significantly more trips in areas with a medium or high social status for the regular MOIA services in 2019 and 2020, there is no significant influence of the social status during the night service. This could be related to the reduced fare during the night service, as the fare was limited to 4 €and public transport ticket holders did not have to pay for a ride at all. The hours of service (12 a.m. to 6 a.m.) could be another reason for this observation, as different people are traveling at night during a pandemic than during MOIA's regular daytime service.

5.2 | Spatial Durbin Error Model

While OLS regression provides a good understanding of the global effects of each independent variable, it treats the effects of each variable as linear and does not account for spatial spillover effects and autocorrelation in the data. Therefore, a spatial regression model is presented here after identifying spatial autocorrelation.

As shown in Section 4, Moran's I and the Lagrange Multiplier tests indicated the necessity to take the spatial pattern into account, and the SDEM was found to be the most suitable for the given data. Results are given in Table 4.

We observe lower AIC and BIC values than for the OLS regression of all six models, which indicates a better

TABLE 4 SDEM results

	2019		Night service		2020	
	Origin	**Destination**	**Origin**	**Destination**	**Origin**	**Destination**
Intercept	53.4	−12.1	15.4	20.5*	−147.1	−174.7
Inhabitants $\frac{1}{1000}$	153.5***	178.2***	20.0***	19.6***	197.2***	210.7***
Workplaces $\frac{1}{1000}$	70.7***	69.8***	1.7***	5.3***	45.0***	49.6***
Hospital beds $\frac{1}{1000}$	286.2	298.9	2.8	80.5***	407.6***	453.4***
Rail stops	12.4	11.3***	8.1***	6.1***	24.8*	32.2**
Long-distance station	1,944.4***	2,003.6***	19.5	25.9	1,466.0***	1,505.5***
Gastronomy	76.4***	68.6***	1.4***	0.8***	39.4***	35.0***
Shopping	−15.2***	−17.0***	−0.1	−0.6**	−1.5	−1.4
Airport	29,024.6***	25,356.9***	−16.8	116.4***	8,619.4***	8,030.8***
Cars per inhabitant	−7.5	−73.0	−18.8**	−26.9***	−96.0	−144.9
Social status high	258.6*	310.0**	−13.7***	−9.0*	197.0***	220.2***
Social status medium	191.6*	249.3**	−3.5	0.3	195.5***	219.2***
Social status low	−18.7	60.4	1.1	5.0	55.7	84.1
Social status very low	0	0	0	0	0	0
Social status missing	159.7	229.3	−8.8*	1.4	184.4**	224.3***
Lag X variables						
Inhabitants $\frac{1}{1000}$	44.1	31.2	5.7***	2.5	54.9*	34.4
Workplaces $\frac{1}{1000}$	14.9	6.4	4.4***	2.9**	49.2***	48.1***
Hospital beds $\frac{1}{1000}$	571.0	790.3	55.9*	9.1	100.9	289.9
Rail stops	−234.1***	−237.5***	1.9	0.9	−134.9***	−117.0***
Long-distance station	163.8	197.0	−69.8	−73.4	242.1	369.3
Gastronomy	15.2**	14.8**	−0.2	−0.1	6.0	3.1
Shopping	26.2**	24.4**	−0.9	−1.9***	9.3	10.9
Airport	−934.3	−1,466.9	−27.5	−121.7	−1,323.9	−1,182.8
Cars per inhabitant	−1,466.4***	−1,308.6***	−61.1***	−36.2**	−922.4***	−765.8***
Social status high	580.5*	600.7**	11.9	8.4	455.0***	430.7***
Social status medium	179.8	205.4	13.0	5.7	226.5*	226.1*
Social status low	165.0	206.3	−2.4	−3.6	46.1	94.1
Social status very low	0	0	0	0	0	0
Social status missing	198.9	262.5	−1.2	−14.2	135.8	135.5
λ	0.48***	0.36***	0.53***	0.43***	0.65***	0.60***
AIC	10,139.4	10,148.4	11,470.0	11,556.9	12,639.2	12,578.6
BIC	10,269.2	10,278.3	11,617.0	11,703.9	12,777.7	12,717.0

1Significance indicators: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

statistical fit of the SDEM. The estimated λ is significant for all models and incorporates the spatial error within the models. This shows that the unexplained variation in ride-pooling demand is highly correlated.

The SDEM estimates, in addition to the direct effects, the local spillover effect of an independent variable of a zone on the dependent variable of a neighboring zone, namely the spatially lagged X.

The direct effects of the model do not differ decisively from the OLS model. A notable difference is that the direct effect of the car ownership rate is not significant for the 2019 and 2020 dataset but the negative local spillover effect of the car ownership rate is highly significant with all three services. Apparently, a high car ownership rather influences the ride-pooling demand in an entire neighborhood instead of the demand in the zone itself.

Significant positive spillover effects of the number of workplaces on origins and destinations of the night service as well as the regular MOIA service in 2020 can be found, indicating a higher spread of demand around business districts than around residential areas.

Long-distance stations show no significant spillover effects, and rail stops even show significant negative spillover effects,

TABLE 5 Estimated bandwidths minimizing AIC in meter

	Origin	Destination
2019	5,670	5,513
Night service	9,845	6,260
2020	5,111	5,111

suggesting that areas near rail stations are less attracted to ride-pooling demand. In contrast, the stations themselves, especially those serving long-distance trains, are very attractive and potentially attract customers for intermodal trips. No spillover effects are observed during night service.

Another significant spillover effect can be observed for the social status in the model estimated for the data from 2020, showing that not only zones with a high social status attract many ride-pooling trips but also the zones around them. The model does not show any highly significant direct or indirect effects of the social status on demand during the night service.

5.3 | Geographically weighted regression model

Finally, a GWR model was estimated to get a comprehensive understanding of the parameter variance within each time period and to identify spatial anomalies. First, the bandwidths of each model was defined minimizing the AIC, which indicates a good model fit. The bandwidths of the six models are given in Table 5.

Five of the six bandwidths are in the range of 5,100 m to 6,300 m. In order to allow a fair comparison across all models, a single bandwidth was defined as the median of the six values, 5,592 m. This bandwidth was used to estimate GWR models for origins and destinations in all three time periods. For simplicity, only the results with trip destinations as dependent variable are reported here. Table 6 shows the GWR model results for the three time periods. The quartiles for each parameter's distribution in the local regression models are reported, which reveals the range of each variable's impact. Also the results of the global OLS model are reported. Note that the bandwidth of over 5 km does not allow to identify spatial patterns in neighborhoods but rather at the district level.

Although the global impact of inhabitants has increased from 2019 to 2020, the impact has decreased in certain areas as we observe a smaller minimum impact. For the workplaces, we observe similar minimum and maximum values but lower parameters between the first and the third quartile, being responsible for the global decline. At each time period, in at least quarters of the study area, hospital beds had a positive impact on ride-pooling destinations. The effects increased throughout the city in 2020 as each quartile's impact increased. It is noteworthy that even during the night service, hospital beds had a negative impact on demand in some parts of the city.

Rail stops and long-distance stations have a positive impact in all time periods in almost all local models. A similarly consistent direction of impact is observed for gastronomy and shopping facilities as the sign of their impact is the same in all local models. For the car ownership variable an increased negative global impact and also a higher variance is observed in 2020 compared to 2019. A detailed spatial investigation revealed that the highest negative impact of high car ownership occurs in the north-eastern and western suburban areas of the city. These areas are characterized by a predominantly high social status and high car ownership. Due to the service area extension in 2020, areas even further away from the city were covered, which likely causes the increase in negative impact of car ownership. This negative impact is much lower in the city center. The results for the social status and the airport are consistent with observations from the global OLS model and show a reasonable variance around the global value.

The results with trip origins as dependent variable are provided in Table A.1 in the appendix.

6 | DISCUSSION

The developments in the mobility sectors in light of COVID-19 have led to discussions about the potential implications for future mobility systems. In this paper, we asked how analyses of historic demand data for ride-pooling can provide some hints in this regard. Looking at the ride-pooling demand development in both 2019 and 2020 at similar rates reveals an interesting hint regarding the potential recovery of ride-pooling services after the first lockdown due to the pandemic. These results are consistent with findings from surveys conducted in Spain, the U.S., and Egypt in 2020 [34, 35, 49], where fear of contagion with COVID-19 was reported but no dramatic decrease in willingness to use on-demand ride-hailing or ride-pooling services was found. Our analysis shows that the proportion of pooled MOIA trips actually increased during the pandemic, and clients reported feeling safer in MOIA vehicles than in public transportation. This suggests acceptance of some exposure to other passengers in ride-pooling, and is further related to measures taken by the provider to increase customers' perception of hygiene and safety on their rides [6].

By analyzing characteristics of ride-pooling demand not only in the course of but also beyond the first COVID-19 lockdown phase, this study shows *why* there is no drastic decrease in ride-pooling usage and how demand characteristics changed. The determinants inhabitants, workplaces, gastronomy, airport and rail stop are found to have a positive impact on ride-pooling demand throughout almost all considered time periods, whereas high car ownership impacts demand negatively. In that, we confirmed the results from a previous study on the spatiotemporal characteristics of pre-pandemic MOIA demand [14].

However, the effect sizes differ throughout the scenarios. In the course of COVID-19, attraction of gastronomic facilities and the airport is reduced. The gastronomy industry faced difficult regulations during the pandemic, which led to a decrease in leisure travel. A decreased leisure and business travel resulted in a near total shutdown of air travel in April and May 2020, which recovered only slowly [48]. This caused a decline in ride-pooling trips to or from the airport. The impact of workplaces decreased over time, which may be caused by an

TABLE 6 GWR model results with trip destinations as dependent variable

		Min.	1st Qu.	Median	3rd Qu.	Max.	Global
Intercept	**2019**	−245.9	−177.9	−125.6	−66.0	32.6	−101.2
	Night service	9.0	13.2	16.4	20.6	58.0	18.1
	2020	−238.9	−204.7	−161.6	−69.8	87.8	−124.4
Inhabitants $\frac{1}{1000}$	**2019**	171.7	201.6	211.2	219.0	227.7	195.7
	Night service	6.0	20.7	24.7	26.0	27.0	19.9
	2020	156.3	226.0	248.2	262.8	268.7	225.1
Workplaces $\frac{1}{1000}$	**2019**	48.2	58.3	63.9	69.8	94.6	61.2
	Night service	2.8	4.3	4.6	5.2	13.1	5.5
	2020	47.9	51.3	52.9	55.2	94.9	55.4
Hospital beds $\frac{1}{1000}$	**2019**	−82.8	125.1	218.5	311.4	461.5	274.2
	Night service	−33.6	80.8	102.6	118.5	131.2	83.2
	2020	−33.3	307.6	424.2	532.1	593.8	405.1
Rail stops	**2019**	11.3	20.1	32.6	48.6	72.8	31.8
	Night service	2.0	5.4	6.3	6.8	8.8	6.7
	2020	16.6	33.5	46.3	58.3	74.6	47.8
Long-distance station	**2019**	1,241.6	1,446.3	1,669.4	1,912.0	2,378.9	1,764.8
	Night service	−43.3	25.3	35.9	45.1	114.9	19.0
	2020	997.1	1,130.6	1,225.5	1,404.2	1,861.2	1,347.1
Gastronomy	**2019**	69.1	72.1	73.7	75.4	79.0	76.4
	Night service	0.2	0.5	0.6	0.8	1.6	0.8
	2020	35.2	37.1	39.3	42.4	50.1	39.9
Shopping	**2019**	−27.0	−20.2	−18.0	−16.2	−13.6	−19.6
	Night service	−1.9	−1.1	−0.9	−0.7	−0.3	−1.0
	2020	−10.0	−6.1	−4.6	−3.4	−2.7	−5.2
Airport	**2019**	25,062.3	25,097.9	25,125.7	25,153.2	25,214.1	25,099.6
	Night service	92.4	136.4	143.7	145.6	152.7	145.0
	2020	7,947.9	7,995.7	8,033.1	8,052.8	8,153.2	8,005.7
Cars per inhabitant	**2019**	−553.8	−436.8	−366.9	−311.0	−276.4	−484.2
	Night service	−112.3	−41.8	−30.7	−25.4	−12.3	−37.4
	2020	−803.7	−605.4	−471.8	−339.3	−204.8	−599.4
Social status high	**2019**	279.0	501.0	563.9	619.5	725.9	507.2
	Night service	−26.8	−13.5	−10.6	−6.0	5.8	−7.4
	2020	209.0	416.4	474.9	506.0	639.1	435.5
Social status medium	**2019**	171.2	285.0	344.6	396.6	437.6	339.4
	Night service	−19.3	−0.7	2.5	5.5	9.2	3.4
	2020	198.5	325.9	367.1	389.7	437.9	368.2
Social status low	**2019**	−20.7	49.5	113.4	192.0	446.5	134.4
	Night service	−17.9	−3.5	5.0	13.2	19.6	4.5
	2020	20.9	129.3	162.7	188.8	237.6	175.4
Social status missing	**2019**	257.0	410.1	465.9	512.9	574.4	453.0
	Night service	−21.7	−4.7	0.3	3.0	10.2	−9.4
	2020	170.6	373.3	432.6	468.8	540.9	425.4

increased shift to teleworking [24, 29, 30, 32]. This shift is expected to persist after the pandemic, allowing for the transferability of results to the future [50]. Instead, more MOIA customers traveled from and to hospitals after the first lockdown, which could also be observed for destinations during the MOIA night service. As the night service was designed to also attract nursing staff and medical travel needs, it likely fulfilled the purpose to provide a transport alternative for these trips.

Social status showed no significant effect on demand during the night service. This parameter was interesting because the ride-pooling offerings that were analyzed differed especially with regard to trip fares. While in 2019 and 2020 regular MOIA fares were applied, the night service offering was for free for transit pass holders. It can be assumed that the city's aim—to enrich public transportation during the first lockdown for all transport users—could be achieved. For the regular services in 2019 and 2020, no major change of the influence of social status on demand could be observed. The higher number of trips in high social status zones may be caused by wealthier residents who are more likely to afford MOIA, or by the general higher attractiveness of these zones due to possible parks, water areas, or recreational activities. This finding contrasts with results from the U.S., where ride-pooling is used in low-income areas [7–9]. This is probably due to differences in the mobility systems in Hamburg or other German cities and cities in the U.S. While in Hamburg 26% of all trips are made by car [51], the modal share of private cars is over 80% in most cities of the U.S. [52]. Public transport, on the other hand, is a mass mode in Hamburg, while it is a niche mode in most cities in the U.S. As a result, travelers from all social classes in Hamburg are significantly more accustomed to sharing rides with other travelers. In addition, ride-hailing services, which are used by wealthier or business travelers in the U.S. (e.g. for airport trips), are strictly regulated and less common in Germany. Lastly, the MOIA vehicle is designed specifically for the service in a very comfortable way to replicate the convenience of a private car, which may attract wealthy customers.

High car ownership had a significant negative impact on the use of MOIA. The effect even rose after the first lockdown and indicates a lower willingness to abandon private cars, which supports studies by Eisenmann et al. [31] and Kolarova et al. [32] who found that routines of monomodal car use were consolidated in the course of the pandemic. However, the GWR model revealed spatial anomalies in that the impact was most negative in areas with high car ownership that were part of the service area extension in 2020. This may indicate that convincing car users to take on a more sustainable travel behavior remains challenging. Offering flexible and comfortable mobility options might not be sufficient in this regard, but potentially need to be accompanied by additional measures.

These findings call for municipalities and public authorities to support ride-pooling among other shared mobility modes as a supplement to classic public transportation with fewer contact exposure. Ride-pooling also promises to reduce vehicle kilometers traveled and its concomitant negative effects if private car trips are replaced [3, 4]. In the context of the transport and energy turnaround, it is therefore essential that policies are introduced that help reducing car ownership and usage rates (like parking fees, parking space reduction, or congestion charges).

The significant positive impact of rail stops and long-distance stations on the MOIA usage shows the potential of ride-pooling to enrich multimodal mobility and the reciprocal benefit for public transportation and on-demand mobility, when both offer a reliable and fast transportation option for customers.

The transferability of the results is valid for the following points: Effects such as the reduction of ride-pooling demand with increasing telework or decreasing air travel is consistent with findings from other countries and even applies to other modes of transportation. Similarly, it has already been found in other countries that although shared mobility systems were used significantly less at the beginning of the pandemic, a recovery can be currently noted. Nevertheless, the willingness to use these services may also depend on the respective mobility culture and implemented policies in each country and is therefore transferable to a limited extent. The detailed spatial effects of the regression models are difficult to transfer because city-specific features such as topography, socio-demographic distribution, or the public transportation system comprise the basis for the models. A previous study showed that the spatiotemporal demand characteristics are well transferable to cities with a similar structure in Germany or Europe [14].

AUTHOR CONTRIBUTIONS

Felix Zwick: Conceptualization, data curation, formal analysis, investigation, methodology, software, validation, visualization, writing - original draft, writing - review and editing. Eva Fraedrich: Conceptualization, investigation, validation, writing - original draft, writing - review and editing. Kay Axhausen: Supervision, validation, writing - review and editing.

ACKNOWLEDGEMENTS

The authors thank Christof Pfundstein for providing business analytics insights of the MOIA service and Nico Kuehnel for valuable comments and lively discussions about the estimation of the spatial regression models.

FUNDING INFORMATION

There was no funding for this research besides our employment.

CONFLICT OF INTEREST

It is acknowledged that Eva Fraedrich and Felix Zwick are employed at the ride-pooling provider MOIA.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from MOIA GmbH and BVM Hamburg. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with the permission of MOIA GmbH and BVM Hamburg.

ORCID

Felix Zwick https://orcid.org/0000-0002-4067-4486

REFERENCES

1. Bitkom: Smart City Index 2020. Bundesverband Informationswirtschaft, Telekommunikation und neue Medien e. V., Berlin, (2020). Available from: https://www.bitkom.org/sites/default/files/2020-10/201009_smart-city-index_gesamt.pdf
2. Hamburg: DIGITISING TRANSPORT Hamburg's ITS Strategy: Providing Future Urban Mobility and Logistics Solutions. Freie und Hansestadt Hamburg; Behörde für Wirtschaft, Verkehr und Innovation; Amt Verkehr und Straßenwesen, Hamburg, (2019)
3. Zhu, P., Mo, H.: The potential of ride-pooling in VKT reduction and its environmental implications. Transport. Res. Part D: Transport Environ. 103, 103155 (2022). Available from: https://doi.org/10.1016/j.trd.2021.103155
4. Zwick, F., Kuehnel, N., Moeckel, R., Axhausen, K.W.: Agent-based simulation of city-wide autonomous ride-pooling and the impact on traffic noise. Transport. Res. Part D: Transport Environ. 90, 102673 (2021). Available from: https://linkinghub.elsevier.com/retrieve/pii/S1361920920308580
5. Foljanty, L.: Mapping the global on-demand ridepooling market (2020). https://medium.com/@lukas.foljanty/mapping-the-global-on-demand-ridepooling-market-f8318de1c030
6. Zwick, F., Fraedrich, E., Kostorz, N., Kagerbauer, M.: Ridepooling als ÖPNV-Ergänzung - Der MOIA-Nachtservice während der Corona-Pandemie. Internationales Verkehrswesen (72), 84–88 (2020)
7. Hou, Y., Garikapati, V., Weigl, D., Henao, A., Moniot, M., Sperling, J.: Factors influencing willingness to pool in ride-hailing trips. Transp. Res. Rec. 2674 (5), 419–429 (2020). http://journals.sagepub.com/doi/10.1177/0361198120915886
8. Soria, J., Stathopoulos, A.: Investigating socio-spatial differences between solo ridehailing and pooled rides in diverse communities. J. Transport Geography 95, 103148 (2021)
9. Dean, M.D., Kockelman, K.M.: Spatial variation in shared ride-hail trip demand and factors contributing to sharing: Lessons from Chicago. J. Transport Geography 91, 102944 (2021)
10. Brown, A.: Redefining car access: ride-hail travel and use in los angeles. J. American Planning Assoc. 85 (2), 83–95 (2019). Available from: https://www.tandfonline.com/doi/abs/10.1080/01944363.2019.1603761
11. Malik, J., Alemi, F., Circella, G.: Exploring the factors that affect the frequency of use of ridehailing and the adoption of shared ride-hailing in california. Transport. Res. Record: J. Transport. Res. Board 2675 (5), 120–135 (2021). https://journals.sagepub.com/doi/abs/10.1177/0361198120985151
12. Gehrke, S.R., Huff, M.P., Reardon, T.G.: Social and trip-level predictors of pooled ride-hailing service adoption in the Greater Boston region. Case Studies Transp. Policy 9(3), 1026–1034 (2021)
13. Aberle, C.: Who benefits from mobility as a service? A GIS-based investigation of the population served by four ride-pooling schemes in Hamburg, Germany. KN - J. Cartography Geographic Inf. 70 (1), 25–33 (2020). Available from: http://link.springer.com/10.1007/s42489-020-00041-4
14. Zwick, F., Axhausen, K.W.: Ride-pooling demand prediction: A spatiotemporal assessment in Germany. J. Transp. Geography 100, 103307 (2022). https://linkinghub.elsevier.com/retrieve/pii/S0966692322000308
15. Weckström, C., Mladenović, M.N., Ullah, W., Nelson, J.D., Givoni, M., Bussman, S.: User perspectives on emerging mobility services: Ex post analysis of Kutsuplus pilot. Res. Transport. Business Manag. 27, 84–97 (2018)
16. Knie, A., Ruhrort, L.: Ride-Pooling-Dienste und ihre Bedeutung für den Verkehr. Nachfragemuster und Nutzungsmotive am Beispiel von, CleverShuttle"; 2020. https://bibliothek.wzb.eu/pdf/2020/iii20-601.pdf
17. Kagerbauer, M., Kostorz, N., Wilkes, G., Dandl, F., Engelhardt, R., Glöckl, U., et al.: Ridepooling in der Modellierung des Gesamtverkehrs - Methodenbericht zur MOIA Begleitforschung, Karlsruher Institut für Technologie, (2021). https://publikationen.bibliothek.kit.edu/1000141282
18. Hörl, S., Zwick, F.: Traffic uncertainty in on-demand high-capacity ride-pooling (2021). 101st Meeting of the Transportation Research Board (TRB). https://hal.archives-ouvertes.fr/hal-03405574/
19. Zwick, F., Kuehnel, N., Hörl, S.: Shifts in perspective: Operational aspects in (non-)autonomous ride-pooling simulations (2022). Transportation Research Part A: Policy and Practice 165, 300-320 https://doi.org/10.1016/j.tra.2022.09.001
20. Zwick, F., Axhausen, K.W.: Impact of service design on urban ridepooling systems. In: 2020 IEEE Intelligent Transportation Systems Conference (ITSC). IEEE (2020)
21. Gilibert, M., Ribas, I., Maslekar, N., Rosen, C., Siebeneich, A.: Mapping of service deployment use cases and user requirements for an on-demand shared ride-hailing service: MOIA test service case study. Case Studies Transp. Policy 7 (3), 598–606 (2019). https://linkinghub.elsevier.com/retrieve/pii/S2213624X18304036
22. Kostorz, N., Fraedrich, E., Kagerbauer, M.: Usage and user characteristics-insights from MOIA, Europe's largest ridepooling service. Sustainability 13 (2), 958 (2021). https://www.mdpi.com/2071-1050/13/2/958
23. Oliver, N., Oliver, N., Lepri, B., Lepri, B., Sterly, H., Lambiotte, R., et al.: Mobile phone data for informing public health actions across the COVID-19 pandemic life cycle. American Association for the Advancement of Science 6(23), eabc0764 (2020). https://www.science.org/doi/full/10.1126/sciadv.abc0764
24. Molloy, J., Schatzmann, T., Schoeman, B., Tchervenkov, C., Hintermann, B., Axhausen, K.W.: Observed impacts of the Covid-19 first wave on travel behaviour in Switzerland based on a large GPS panel. Transport Policy 104, 43–51 (2021)
25. Heiler, G., Reisch, T., Hurt, J., Forghani, M., Omani, A., Hanbury, A., et al.: Country-wide mobility changes observed using mobile phone data during COVID-19 pandemic. In: Proceedings - 2020 IEEE International Conference on Big Data, Big Data 2020, pp. 3123–3132. Institute of Electrical and Electronics Engineers Inc., Piscataway (2020)
26. Yabe, T., Tsubouchi, K., Fujiwara, N., Wada, T., Sekimoto, Y., Ukkusuri, S.V.: Non-compulsory measures sufficiently reduced human mobility in Tokyo during the COVID-19 epidemic. Sci. Rep. 10 (1), 1–9 (2020). https://www.nature.com/articles/s41598-020-75033-5
27. Santamaria, C., Sermi, F., Spyratos, S., Iacus, S.M., Annunziato, A., Tarchi, D., et al.: Measuring the impact of COVID-19 confinement measures on human mobility using mobile positioning data. A European regional analysis. Safety Science 132, 104925 (2020)
28. Kucharski, R., Cats, O., Sienkiewicz, J.: Modelling virus spreading in ride-pooling networks. Sci. Rep. 11 (1), 1–11 (2021). Available from: https://www.nature.com/articles/s41598-021-86704-2
29. de Haas, M., Faber, R., Hamersma, M.: How COVID-19 and the Dutch 'intelligent lockdown' change activities, work and travel behaviour: Evidence from longitudinal data in the Netherlands. Transp. Res. Interdiscip. Perspect. 6, 100150 (2020)
30. Borkowski, P., Jażdżewska.Gutta, M., Szmelter.Jarosz, A.: Lockdowned: Everyday mobility changes in response to COVID-19. J. Transp. Geography 90, 102906 (2021)
31. Eisenmann, C., Nobis, C., Kolarova, V., Lenz, B., Winkler, C.: Transport mode use during the COVID-19 lockdown period in Germany: The car became more important, public transport lost ground. Transp. Policy 103, 60–67 (2021). Available from: https://doi.org/10.1016/j.tranpol.2021.01.012
32. Kolarova, V., Eisenmann, C., Nobis, C., Winkler, C., Lenz, B.: Analysing the impact of the COVID-19 outbreak on everyday travel behaviour in Germany and potential implications for future travel patterns. Eur. Transp. Res. Rev. 13 (1), 1–11 (2021). https://etrr.springeropen.com/articles/10.1186/s12544-021-00486-2
33. Loder, A., Bressan, L., Wierbos, M.J., Becker, H., Emmonds, A., Obee, M., et al.: How many cars in the city are too many? Towards finding the optimal modal split for a multi-modal urban road network. Front. Future Transport. 2, 5 (2021)
34. Jabbari, P., MacKenzie, D.: Ride sharing attitudes before and during the COVID-19 pandemic in the united states. Findings, pp. 1–6 (2020). https://findingspress.org/article/17991-ride-sharing-attitudes-before-and-during-the-covid-19-pandemic-in-the-united-states
35. Gaber, H.R., Elsamadicy, A.M.: What drives customers to continue using ride-sharing apps during the COVID-19 pandemic? The case of

Uber in Egypt. Cogent Business and Management 8(1), (2021). http://doi.org/10.1080/23311975.2021.1944009 https://creativecommons.org/licenses/by/4.0/www.econstor.eu
36. Wang, W., Miao, W., Liu, Y., Deng, Y., Cao, Y.: The impact of COVID-19 on the ride-sharing industry and its recovery: Causal evidence from China. Transport. Res. Part A: Policy Pract. 155, 128–141 (2022)
37. Zhang, W., Liu, L.: Exploring non-users' intention to adopt ride-sharing services: taking into account increased risks due to the COVID-19 pandemic among other factors. Transport. Res. Part A: Policy Pract. 158, 180–195 (2022). https://linkinghub.elsevier.com/retrieve/pii/S0965856422000519
38. OpenStreetMap Contributors: OpenStreetMap (2020). https://www.openstreetmap.org
39. Staatsarchiv Hamburg, Behörde für Kultur und Medien, (2020). http://transparenz.hamburg.de/
40. Transport model of the city of Hamburg. Hamburg: Behörde für Verkehr und Mobilitätswende, (2018)
41. Freie und Hansestadt Hamburg - Behörde für Stadtentwicklung und Wohnen.: Sozialmonitoring - Integrierte Stadtteilentwicklung - Bericht (2019)
42. Moran, P.A.P.: Notes on continuous stochastic phenomena. Biometrika 37 (1/2), 17 (1950). https://www.jstor.org/stable/2332142?origin=crossref
43. Anselin, L.: Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. Geog. Anal. 20 (1), 1–17 (1988). http://doi.wiley.com/10.1111/j.1538-4632.1988.tb00159.x
44. Anselin, L.: Spatial econometrics: methods and models. In: Studies in Operational Regional Science, Vol. 4. Springer Netherlands, Dordrecht, (1988). http://link.springer.com/10.1007/978-94-015-7799-1
45. LeSage, J., Pace, R.K.: Introduction to Spatial Econometrics. Chapman and Hall/CRC, Boca Raton (2009). Available from: https://www.taylorfrancis.com/books/9781420064254
46. Brunsdon, C., Fotheringham, A.S., Charlton, M.E.: Geographically weighted regression: a method for exploring spatial nonstationarity. Geog. Anal. 28 (4), 281–298 (1996). Available from: https://onlinelibrary.wiley.com/doi/full/10.1111/j.1538-4632.1996.tb00936.x
47. Fotheringham, A.S., Brunsdon, C., Charlton, M.: Geographically Weighted Regression: The Analysis of Spatially Varying Relationships. Wiley, Chichester (2002)
48. Sun, X., Wandelt, S., Zheng, C., Zhang, A.: COVID-19 pandemic and air transportation: Successfully navigating the paper hurricane. J. Air Transp. Manag. 94, 102062 (2021)
49. Awad Núñez, S., Julio, R., Gomez, J.Moya. Gómez, B., González, J.S.: Post-COVID-19 travel behaviour patterns: impact on the willingness to pay of users of public transport and shared mobility services in Spain. Eur. Transp. Res. Rev. 13 (1), 1–18 (2021). https://etrr.springeropen.com/articles/10.1186/s12544-021-00476-4
50. de Palma, A., Vosough, S., Liao, F.: An overview of effects of COVID-19 on mobility and lifestyle: 18 months since the outbreak. Transport. Res Part A: Policy Pract. 159, 372–397 (2022)
51. Mobilität in Deutschland MiD Regionalbericht Stadt Hamburg. Bundesministerium für Verkehr und digitale Infrastruktur, (2020). https://www.mobilitaet-in-deutschland.de
52. Mcguckin, N., Fucci, A.: Summary of Travel Trends: 2017 National Household Travel Survey. Federal Highway Administration, (2018). https://nhts.ornl.gov/

How to cite this article: Zwick, F., Fraedrich, E., Axhausen, K.W.: Ride-pooling in the light of COVID-19: Determining spatiotemporal demand characteristics on the example of MOIA. IET Intell. Transp. Syst. 17, 1166–1181 (2023). https://doi.org/10.1049/itr2.12293

APPENDIX: A

TABLE A.1 GWR model results with trip origins as dependent variable.

		Min.	1st Qu.	Median	3rd Qu.	Max.	Global
Intercept	**2019**	−207.9	−134.8	−93.8	−32.5	85.8	−68.2
	Night service	5.2	9.1	13.2	23.5	55.7	18.4
	2020	−283.1	−216.4	−161.8	−56.5	137.2	−120.1
Inhabitants $\frac{1}{1000}$	**2019**	133.3	181.1	196.4	206.4	213.1	175.9
	Night service	6.3	21.4	25.8	28.1	29.6	21.0
	2020	137.1	219.3	246.2	266.6	274.4	220.7
Workplaces $\frac{1}{1000}$	**2019**	47.6	58.1	64.1	71.2	88.5	61.2
	Night service	0.8	1.2	1.4	2.0	6.4	2.3
	2020	40.4	43.9	45.6	48.4	90.0	48.6
Hospital beds $\frac{1}{1000}$	**2019**	−111.6	133.6	240.6	362.1	638.8	327.4
	Night service	−31.0	2.8	14.4	21.1	26.1	1.3
	2020	−105.5	310.8	442.6	554.9	622.2	406.7
Rail stops	**2019**	14.9	24.0	34.6	49.3	68.3	31.6
	Night service	2.8	8.9	10.1	10.6	11.1	9.7
	2020	15.6	35.6	43.2	52.3	64.2	42.7
Long-distance station	**2019**	1,093.0	1,341.2	1,575.3	1,815.3	2,267.9	1,664.5
	Night service	−23.3	8.9	13.1	23.5	92.3	3.4
	2020	953.0	1,069.0	1,164.8	1,311.1	1,780.3	1,289.3

(Continues)

TABLE A.1 (Continued)

		Min.	1st Qu.	Median	3rd Qu.	Max.	Global
Gastronomy	**2019**	81.9	83.2	84.0	85.0	88.3	86.6
	Night service	0.7	1.2	1.4	1.6	2.4	1.6
	2020	40.7	43.0	45.4	49.4	57.6	46.1
Shopping	**2019**	−26.7	−19.4	−17.8	−16.4	−13.5	−19.2
	Night service	−1.5	−0.6	−0.3	−0.1	0.8	−0.5
	2020	−15.0	−8.4	−5.9	−3.9	−2.7	−6.6
Airport	**2019**	28,652.1	28,693.9	28,722.2	28,749.9	28,825.5	28,685.8
	Night service	−37.5	−5.9	2.1	5.7	28.4	5.1
	2020	8,492.5	8,556.0	8,609.0	8,634.1	8,728.5	8,576.6
Cars per inhabitant	**2019**	−735.2	−480.0	−410.4	−342.2	−287.6	−565.5
	Night service	−94.7	−47.8	−35.9	−28.2	−20.8	−43.8
	2020	−852.6	−676.4	−536.5	−357.2	−183.3	−661.3
Social status high	**2019**	222.0	462.4	544.9	620.3	768.7	482.4
	Night service	−33.4	−15.7	−10.8	−7.9	6.2	−9.5
	2020	182.7	425.7	498.4	541.9	704.1	447.8
Social status medium	**2019**	122.1	238.9	303.6	353.5	430.8	310.8
	Night service	−29.2	2.2	5.8	8.1	10.2	4.7
	2020	172.6	325.2	376.5	403.6	471.2	376.7
Social status low	**2019**	−93.8	−21.4	31.2	85.7	277.8	59.2
	Night service	−21.5	3.8	6.1	7.7	14.8	3.4
	2020	−10.0	101.9	140.5	173.5	242.6	161.5
Social status missing	**2019**	199.9	361.9	427.7	482.2	576.7	434.2
	Night service	−26.9	−6.8	−1.7	0.2	2.0	−12.7
	2020	138.3	372.4	446.1	487.6	573.6	435.7