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# Impact of the COVID-19 pandemic on bike-sharing use in Toulouse

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## 1 Abstract

Urban areas have been dramatically confronted with the rapid spread of the COVID-19 pandemic. As one of the most noticeable consequences of the pandemic, people have quickly reconsidered their travel options to minimize infection risk. Many studies on the Bike Sharing System (BSS) of several cities have shown that, in this context, cycling appears as a resilient, safe and reliable mobility option. In this paper, we analyze the spatio-temporal effects of the pandemic on BSS in the french city of Toulouse using Exploratory Factor Analysis (EFA). We discuss how this approach enables to highlight different aspects of the change in usage of BSS in the four years surrounding the pandemic, both from a geographical and temporal point of view. We use Origin/Destination data for the four years from 2019 (pre-pandemic), 2020 and part of 2021 (pandemic), and 2022 (post-pandemic). Our results confirm that cycling increased during the pandemic, with rush times remaining exactly the same as during the pre-pandemic year, before returning to the previous standards around 2022 after a notable transitional year 2021. The EFA approach enables to show the differences in these effects in the city center and the periphery of Toulouse.

## 2 Introduction

The rapid spread of the COVID-19 pandemic has brought unprecedented challenges and threatens normal human life and global public health. Since the first case of COVID-19 identified in December 2019 in the city of Wuhan in China, measures have been taken worldwide and at different scales to stop the spread of the virus. They concern of course the field of health (research and administration of vaccines, rapid identification of new clusters, etc.), but also transportation (limitation of international flights, punctual bans on inter-regional transportation, etc.) as human mobility has significantly contributed to virus propagation. In urban areas, many people have voluntarily chosen to avoid using public transport, especially due to difficulties in respect barrier measures when traveling. In this context, individuals have often re-evaluated their travel options

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towards more-isolated modes such as private cars, personal or shared bicycles [BSH<sup>+</sup>20, Buc20]. Considerations of health risks, travel flexibility, traffic reduction, or the desire to spend less money in times of economic crisis entered into individual decisions about transportation. Under these circumstances, several observations show that cycling can be an interesting choice [PCZZ20, FLBA19, SGG<sup>+</sup>18, SZQR22], and, for some, can help the economy to recover quickly. In many cities, public authorities are implementing temporary facilities, strategies derived from “tactical” urban planning, to accompany this increase in cycling [CM20, Sil16]. Bicycle is a largely flexible, inexpensive and easily adaptable mode of urban transport to a wide range of situations, compared to, for example, public transport, whose adaptation is often a longer-term challenge [GC21].

More than three years after the beginning of the pandemic, COVID-19 and its variants no longer constitutes a public health emergency of international concern but are still present throughout the world and the efforts are now more focused on prevention, control and longer-term sustainable management of the disease. Besides the fact that the emergence of new pandemics is a scenario now considered highly probable by the scientific community, feedback from COVID-19 suggests that vaccination alone is inefficient to eradicate such a virus and a fine understanding of the parameters of its diffusion is a key factor [IHN<sup>+</sup>23]. Under these circumstances, it is natural to question the dynamics of bicycle use in urban areas since the pandemic. The effects of the pandemic on urban mobility meet more gradual transformations that have been underway for several decades now, resulting from the awareness of the ecological emergency [SSS<sup>+</sup>22]. These transformations tend to favor public transport and active or “soft” mobilities [Bea14, RRMZ21]. Among these, the bicycle has the advantage over public transport of allowing a certain physical activity, a greater freedom of use, an even greater reduction of environmental impact [ZCL21], and a relatively low cost deployment. On the other hand, its use is now largely dependent on weather, topography and urban environment (speed moderation and bicycle facilities [BIT21]). The development of cycling has been encouraged by the public authorities by setting up Bike Sharing Systems (BSS), adapted infrastructures and, more recently and in some countries, financial incentives for the purchase or repair of bicycles. These policies are part of a new paradigm that advocates sustainable, multimodal mobility (as opposed to the single-mode, infrastructure-focused paradigms of the automobile and public transport). With an interesting flexibility in multimodal trips, BSS uses are strongly related to the connectivity to metro and rail stations [BAUT20] in a noticeably different manner in urban center and suburban areas [WLG<sup>+</sup>21, LJFS20]. However, when possible, door-to-door trips are favoured [FMC15].

Cycling thus appears in several respects to be a resilient and reliable urban mobility option in the short and long term, compatible with both the health crisis as we know it and the objectives of sustainable development. Since mobility habits are difficult to change [Roc15, MIFCM18, BMC22], taking advantage of a change in behavior during the current health crisis, of a cognitive appropriation of cycling sometimes facilitated by the economic situation, to sustainably transform urban mobility practices and habits is an opportunity and a challenge for many cities. The development of BSS is an effective response by public authorities to increase bicycle use in urban areas [DeMo9, SGZ12, HVWM10, PDH10]. For example, in the year following the introduction of BSS in the city of Lyon, a 44% increase in bicycle trips [Büho7] was observed, with 96% new users who had not previously cycled in Lyon’s city center. Similarly, in Paris, cycling increased by 70% with the launch of the Vélib BSS [Nado8, SGZ10]. While effective in the short term, several studies have shown that the development of bike sharing also contributes to a sustainable increase in the cycling population [DeMo9] and that BSS usages are related to bike usages as a whole [PKD21]. Today, a little more than half a century after the first bike-sharing system was implemented in 1965 in Amsterdam, BSS exist in many cities around the world with growing success [SGZ10, MYVOH20, EU20] and often with quite similar technological solutions. BSS appeared in France with a pioneer initiative in La Rochelle in 1976 [HP16] and a fully automated

solution (probably the first in the world) was implemented in Rennes in 1998. But, in France, the generation of BSS as we have it today (with the need for each user to register a personal account) was firstly introduced in Lyon in 2005, followed by Paris and Toulouse in 2007.

The success of BSS all over the world has given rise to a rapid increase in the scientific research on these systems. There have been several literature review papers summarizing the research done in this field [EU20, TSeS21, Fis19, MDC21]. The effect of the pandemic on BSS usage has been widely studied, with data collected from cities all over the world. Some studies use operator data, either Origin/Destination or simply traffic data. Among these are studies comparing five cities in the USA [Tok20], about New-York [TL20, WN21, PCZZ20], Chicago [HXLZ21], Lisbon [TSeS21], London [LZZR21], Seoul [Sun22], Singapore [SZQR21], Zurich [LZHA20], Beijing [CGX]20, SCB<sup>+</sup>21], Kosice Slovakia [KKH21], or Valencia [SPCAG<sup>+</sup>23]. Several other studies are based on online or on-site surveys in Tesseloniki in Greece [NAS20], Lisbon [TC22] in Portugal, San Antonio in the USA [JG21], in several Italian towns [BIT21], distributed in several European towns [MiBSRK22], or with participants from all over the world [BSH<sup>+</sup>20, BLP<sup>+</sup>21, CSS<sup>+</sup>20].

In a recent paper, [SZQR22] [TSMes23] summarizes recent progress in bike-share studies related to COVID-19. They classify the issues into three main domains. The first one focuses on spatio-temporal changing patterns of bike-share usages before and after the pandemic crisis, mainly with data analysis methods applied on BSS data. The second one is more about comparing different modes of transport. The third one is centered on user behaviors via survey analysis. [HKB21] provides an interesting summary of the diversity of published results.

In the present paper, we focus on the spatio-temporal aspect of BSS, a topic on which numerous recent papers have emerged. With a Bayesian time-series model on monthly aggregated data, [HKB21] estimates the impact of the pandemic on both trip duration and number of trips in London. Confirming previous results, in (e.g., [LZZR21, WN21]), the authors observe that trips are longer than expected during and after the spring 2020 lockdown. [SZQR22] uses an original graph theoretical approach for comparing flows of bikes during 4 COVID-relevant period in Singapore. The proposed approach gives an appropriate way to measure the increase of local trips observed during and after the lockdown. [PCZZ20] also uses a graph theoretical approach on New-York BSS data showing the reconfiguration of BSS trips on Manhattan Island during the lockdown. [Tok20] leverages a General Linear Model (GLM) to formalize the association of the month-to-month change of bike-share activity within a geographical tract and its distance from the CBD. Using weekly aggregated data for 6 town in the USA and 6 months, they confirm previous results that the distance to the CBD is positively correlated to BSS usage [FIEEG<sup>+</sup>14, WLSH15, NSG16, YHTC20] and, more, explains significantly well the dynamics of changing due to COVID-19: CBD areas are more responsive to the pandemic with usage declining faster but also recovering faster.

To precisely evaluate the impact of the lockdown (and lockdown ease) on the BSS usage in London, [LZZR21] crosses two models: a segmented regression model and a Bayesian structural time-series model, both on aggregated data at daily level for the period from January 2019 to June 2020. Rainy conditions and BSS 2019 trips are included in the regression model as binary covariates. The authors distinguish the morning and evening peaks from the rest of the day and three levels of travel durations (short, middle, long). Their main findings are that the number of long trips increases during the lockdown and lockdown ease, which is not observed for short trips, and that the lockdown ease has few effects on the morning peak which remains low all along the lockdown. Moreover, immediate effects on BSS usages are more important on highly infected boroughs than in low infected one. With a similar goal of analyzing traffic-bike change during the

lockdown, [BMC22] uses data collected through 13 and 20 bike counters respectively in Basel and Zurich (Swiss). The daily cycling traffic is estimated by Random Forests, separately for the working-days and the weekends. Both models depend on weather, hour of the day and whether the day is a holiday (school or public). Among the main findings, the daily traffic during the lockdown is acknowledged to be more complicated than just a mix between pre-lockdown working and weekend days traffic patterns. It is also found that the bike traffic during the second COVID wave follows the same pattern observed during the first one. After the first lockdown, bike usage increases more in Zurich than in Basel although cycling culture is much better in Basel than in Zurich.

The study reported in [HXLZ21] is very similar to ours. Instead of a log-linear regression model, the authors used Generalized Additive Models (GAMs) for comparing a regular BSS usage between March and July 2019 in Chicago with a pandemic BSS usage for the same period in 2020. They control consider weather conditions, seasonality and holidays effects. Like previous studies, they observe that trips are longer in 2020 than in 2019, and bike-sharing is more resilient than other transport modes. They also show that pandemic impact on bike sharing has a differential impact depending on socio-demographic patterns around each dock-station. [SCB<sup>+</sup>21] proposes a novel method to calculate bikers' trajectories and estimate the environmental benefits during COVID-19. The exact route taken by the cyclists is not trivial to infer. With the same method as the one proposed in [SCB<sup>+</sup>21] for Beijing data, we used OSMnx and OpenStreetMap to calculate shortest paths between origins and destinations for Toulouse BSS data. Checking the "bike" option in OpenStreetMap has been observed to be a bad solution, leading to many highly improbable speeds. Checking the "pedestrian" option proved instead to be a much better approach. It seems to indicate that Toulouse BSS riders are taking shortcuts, not necessarily referenced as cycle routes. In a still ongoing survey in Toulouse, we have asked 125 riders to describe their route and the results show that 88% match well with the "pedestrian" option of OSMnx but the remaining 12% does not follow clear logics. Because of this difficulty, in the following we will not use any hypotheses on the route.

In this paper, we propose a spatio-temporal analysis of COVID-19 effect on BSS usage in Toulouse, France which was among the first cities in the world to implement automated BSS and, therefore, where the use of BSS is well established. For this purpose, we consider 2019 as a baseline year against which we can compare corresponding periods in the following years 2020, 2021 and 2022. To our knowledge, this is the first study of this type on French cities. In contrast to many previous papers, we use several level of data aggregation (week, day, 10 minutes) to improve the accuracy of the results. After describing the data (Section 3), the following section (Section 4) provides general statistics and shows that the number of bikes leaving or returning a dock-station is very well modeled by a log-linear function of time variables and of the rain level. Section 5 uses matrix factorization to highlight the presence of latent explanatory factors, which can for instance depend on the spatial distribution of the stations on the territory, and study their dynamics before, during and after the COVID pandemic. Calculations were made using R software and python language, and maps were produced with QGIS software.

### 3 Data description and context

In Toulouse, a dock-based Bike-Sharing System (BSS) has been installed by JC Decaux in 2007 who shared the anonymous data of all the Origin/Destination trips for the years 2019 to 2022, excluding service operations. Each row of the dataset includes departure and arrival times at a one-minute precision as well as the origin and destination stations. The year 2019 will be considered as a "normal" year, as opposed to 2020

when France faced the onslaught of the first wave of COVID-19. For each year, a record of the dataset contain the positioning and timing information of locking and unlocking of bikes, excluding that of rebalancing operations. Because data are anonymized, it is not possible to follow a user in his/her daily use of BSS. We removed trips with duration less than or equal to 2 min with identical origin and destination, or with a duration more than 12 hours regardless of origin or destination. Following these filters, the data contain 287 different dock-stations with no change between 2019 and 2022 and a total number of trips of 3.83 million in 2019, 2.93 million in 2020 respectively (corresponding to a 23% decrease), 3.45 million in 2021 and 3.95 million in 2022. As expected, the density of dock-stations is higher in the city center (Figure 1).

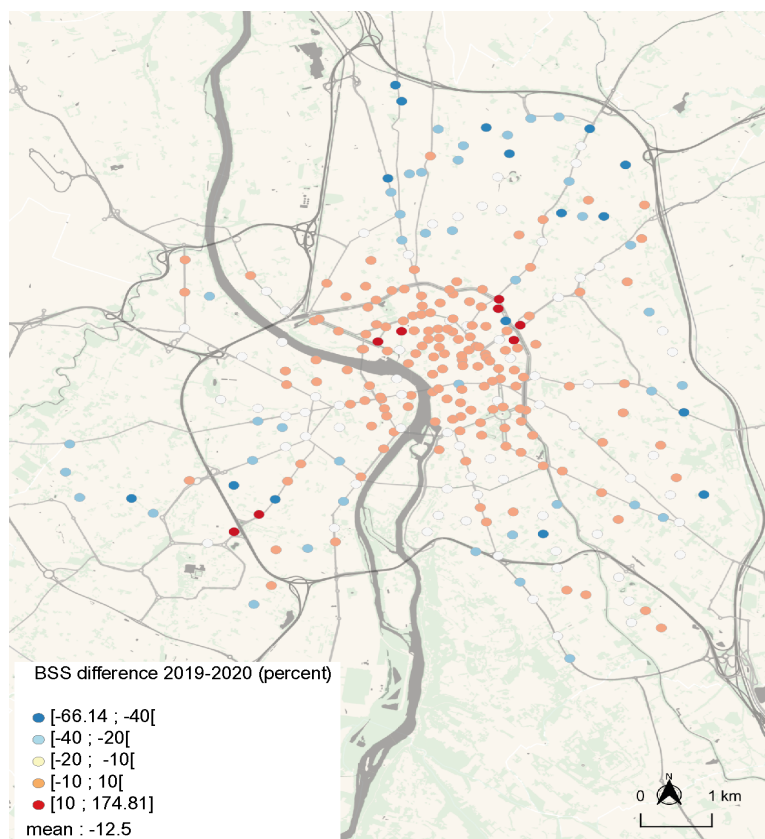
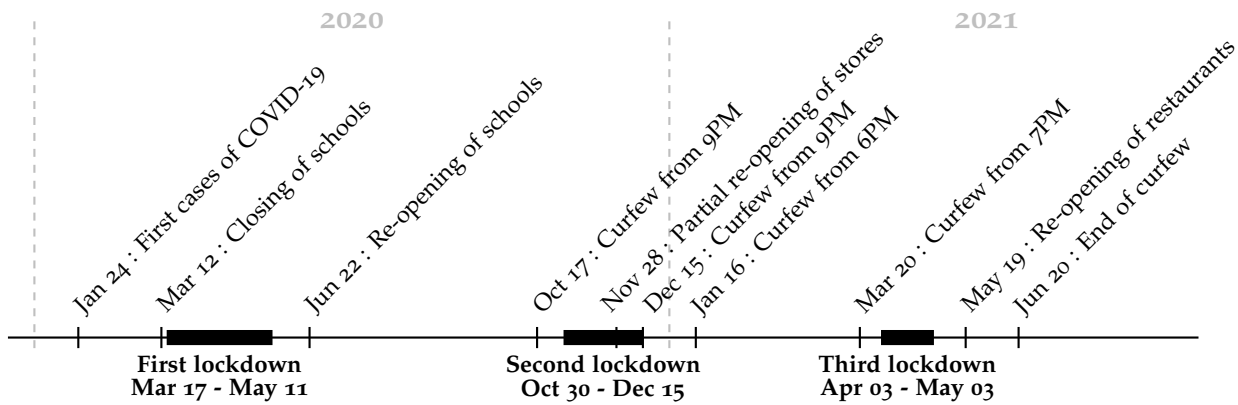


Figure 1: Locations of bike-sharing docks in Toulouse. Each station is colored according to the percentage of traffic increase/decrease from 2019 to 2020. To avoid bias in case a station is out of order for a given period, the corresponding periods of both 2019 and 2020 were dismissed in the calculation of the percentage.

The traffic change between 2019 and 2020 is not homogeneous among the dock-stations: while the city center shows a high decrease of uses, more periphery and residential dock-stations are less impacted and can even show an increasing usage (Figure 1). These observations are consistent with [CGX]20, HXLZ21, Kim21] observations in Beijing, Chicago and Seoul respectively, but in contrast with [HCC+21] results in Nanjing (China).

Weather data from the Blagnac station (closest to Toulouse city-center) were provided by Météo-France at a hourly basis, but are only available for the years 2019 and 2020. The "rain level" variable has the highest negative correlation with BSS usages, which is consistent with previous findings [BPC21].

Regarding the development of the pandemic, the dynamics of intensive care hospitalizations <sup>1</sup> peaked at the end of March 2020, followed by a strong during the 3 summer months (June-July-August) and then rised again at the end of September to reach the peak of the second wave around November 10, 2020. We provide below a short timeline of the main dates of policy interventions in France relative to the pandemic situation.



## 4 Time modeling for citywide bike sharing use

BSS use is measured every 10 minutes over the course of the years 2019 to 2022 yielding a sample of size  $365 \times 144 = 52560$  for 2019, 2021 and 2022 and 52704 for the leap year 2020. The data consist of the raw number of trips over the whole city initiated in each 10 minute segment, without any pre-processing. Temporal bike usage is modeled as a multiplicative function of time and amount of precipitation. The time component accounts for the hour of day (among the 144 10 min segments per day), the type of day (working or weekend day), the week of the year (1 to 53) and holidays. The precipitation variable is divided into three levels according to the duration of rain within the hour: Low (less than 20 min), Medium (between 21 and 40 min) and High (more than 41 min).

The proposed model, in the spirit of [HXLZ21], is as follows

$$BSS \approx f(\text{hour of day, type of day}) \times g(\text{week}) \times h(\text{holidays}) \times \ell(\text{level of precipitation}), \quad (1)$$

The functions  $f$ ,  $g$ ,  $h$  and  $\ell$  are estimated non-parametrically via a linear model on the logarithm of  $BSS$ , with all variables treated as factors. The amount of precipitation was only available for the years 2019 and 2020 and, while it is highly significant in the model these two years, it only accounts for less than 0.5% of explained variance. This variable is removed from the model for the years 2021 and 2022.

<sup>1</sup><https://www.data.gouv.fr/fr/datasets/donnees-hospitalieres-relatives-a-lepidemie-de-covid-19/>

According to the model, holiday induces a mean decrease of 25.65% in BSS use. Similarly, the weather is responsible for a 23.1% decrease in BSS use for a Medium level of precipitation and for a 26.2% in case of a High level, the two coefficients being highly significant. Nevertheless, the overall periodic time components (time of the day, type of day and week) accounts for more than 96% of explained variance, compared to less than 1% for holidays and precipitations.

Since the data are measured every 10 minutes, the estimation of the first function  $f$  accounts for 144 parameters associated to the typical BSS use distribution during a working day (one for every 10 minute segment) and 144 parameters for the distribution over a weekend day. The remaining parameters correspond to the weekly evolution along the year (53 values) represented by the function  $g$ , an additional parameter adjusting for the 11 holidays of the year and 3 parameters for the three levels of precipitations. Accounting for identifiability, we reach a total of 343 parameters for 52217 degrees of freedom for 2019, 2021 and 2022, and 52361 for the leap year 2020. The  $R^2$  in the linear model varies between 0.97 and 0.99 for the four years considered. Nearly all parameters are highly significant (p-value  $< 10^{-16}$ ) with the very few exceptions corresponding to night values with very low BSS use.

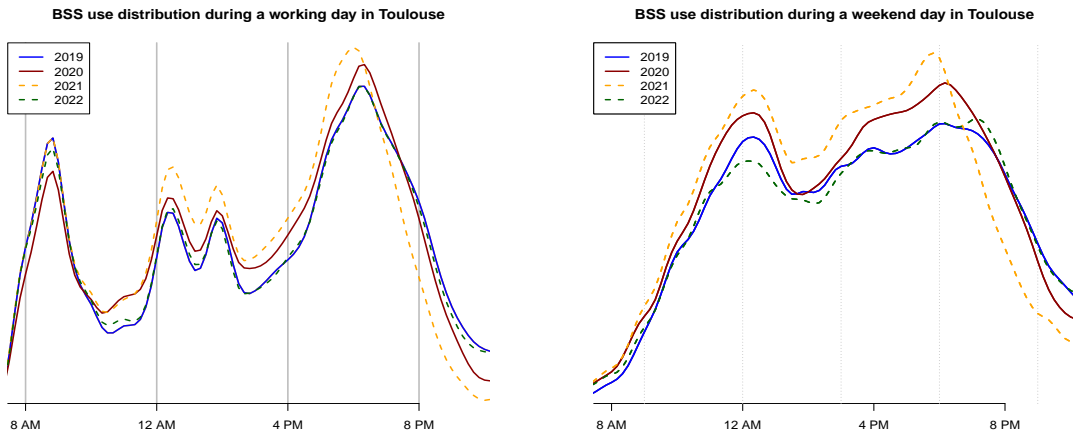


Figure 2: Distribution of the BSS use over the course of a working-day and weekend-day in Toulouse, as fitted by the model.

Figure 2 show the values of the function  $f$  of Equation (1) for working days and weekend days, as fitted by the model for each year. The very high  $R^2$  in each model suggests that these distributions are representative of the patterns of BSS use over the course of one day throughout the year, after correcting for holidays (and meteo conditions for 2019 and 2020). These curves are normalized so as to have a unit underneath area, so as to represent the distribution of BSS use over the day, independently of the total amount of BSS use, which is represented in Figure (4) as a weekly variation throughout the year.

These distributions strongly suggest that the changes in BSS use caused by the pandemic took two years to go back to original, both for working days and weekends. Indeed, after a transition during the year 2021, whose pattern goes even further away than the year 2020 of the pandemic, the year 2022 returns to a nearly



exact replica of 2019. To quantify the proximity of the different periods of time, we use the  $\mathbb{L}^1$  distance between each pair of functions (normalized so as to have an area under curve of one). We measure a  $\mathbb{L}^1$  distance of around 0.02 between the years 2019 and 2022 compared to 0.10 between 2019 and 2021 and 0.17 between 2019 and 2022. Similarly for weekend days, the  $\mathbb{L}^1$  distance to the year 2019 preceding the pandemic are around 0.13 for 2020, 0.23 for 2021 while only 0.03 for 2022.

For working days, the four visible traffic peaks occur at nearly the exact same time each year, namely around 8:45 AM, 12:15 PM, 1:45 PM and 6:15 PM. We observe nonetheless a change in behavior in 2020, with a small decrease of the 8:45 AM peak compensated by a higher and more spread out use during the late morning and the beginning of the afternoon compared to 2019. This change is amplified in 2021 before going back to the pre-pandemic standard in 2022.

The decrease of BSS use in the morning rush during the pandemic situation was observed in previous studies but often more pronounced [HXLZ21, BMC22, KKH21, LZHA20]. In these papers, the morning peak completely disappears during the pandemic, contrary as what we observe in Toulouse when focusing on the lockdown periods, see Figure 3. The relative increase of BSS use we observe around noon exists in some of these papers but a normalization of the data would be necessary to highlight them. What is surprising, however, is the absence of two peaks around noon in all the previous studies. It may reflect different habits, or just the fact that these studies consider data with a one-hour precision, whose effect is to aggregate the two peaks.

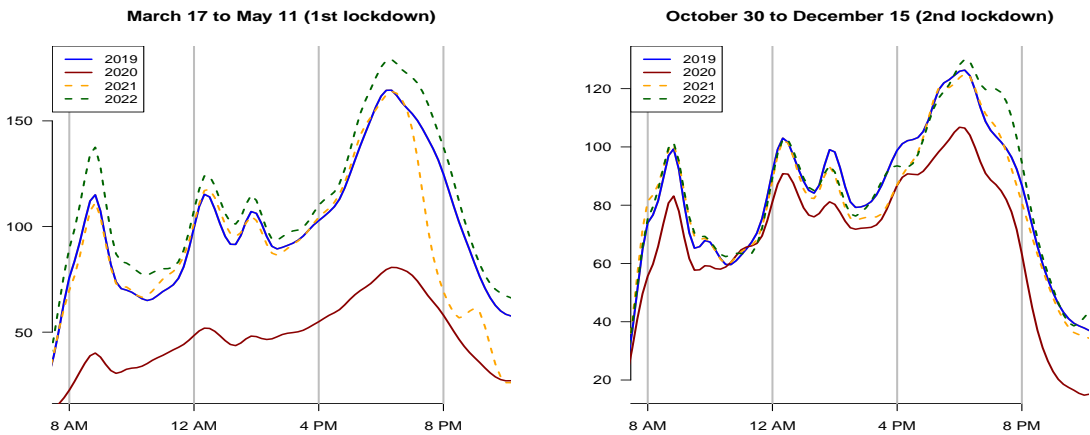


Figure 3: Comparison of the average BSS use during a working-day Toulouse during the two 2020 lockdown periods.

In spite of the high quality of fit, Figure 3 shows high variations of BSS use over the course of a day in 2020 during the two lockdowns. The left graph shows that the heavy restrictions of the first lockdown in France almost completely obliterated the BSS use. Nevertheless, three of the four peaks are still discernible and occur at the exact same times, around 8:45 AM and 6:15 PM. The impact of the second lockdown was much less noticeable than the first one with a similar day pattern as usual and only a moderate decrease in volume. It is interesting to notice that, with or without COVID, the morning peak for working-days is, for this period of the year, preceded by a smaller one around 8 AM. This small peak, somehow present in the

March-May period in 2019, reveals a bimodal distribution which probably deserves to be studied in more detail.

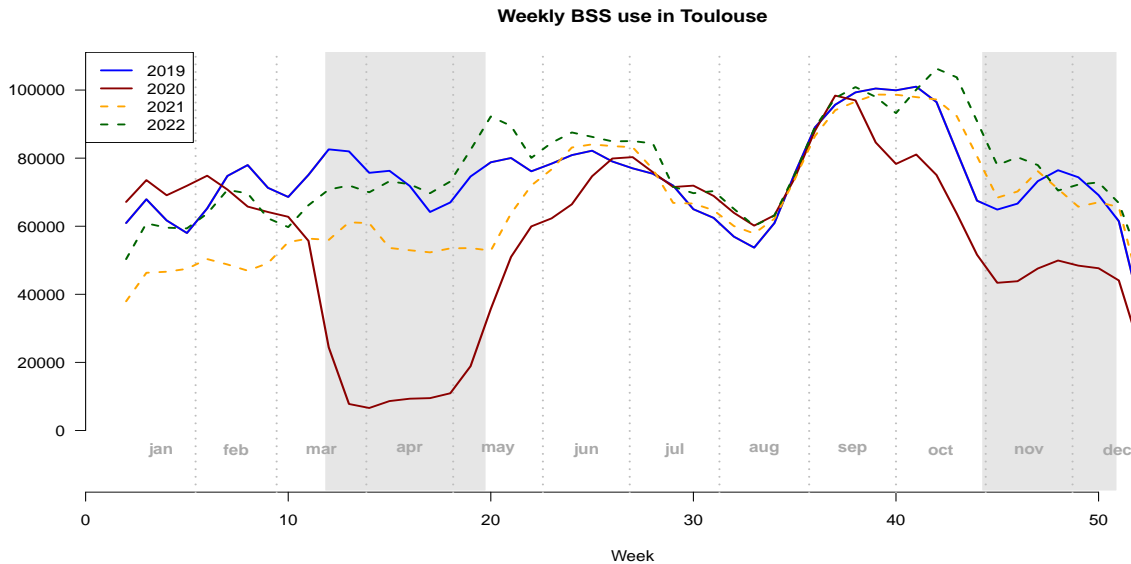
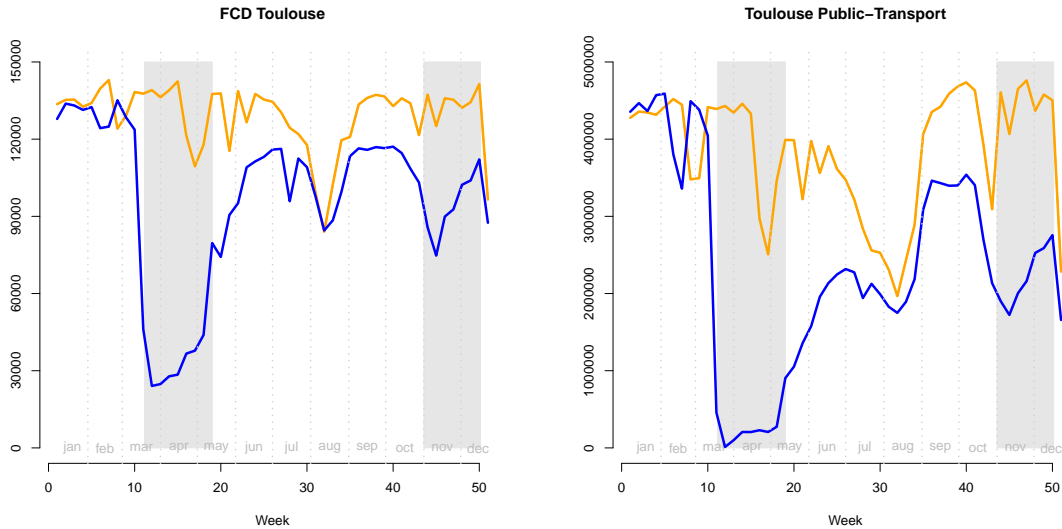


Figure 4: Weekly evolution of BSS use over the course of the years 2019 to 2022 in Toulouse as fitted by the model. Curves are normalized so that the total use over the year is equal to the observed value. The lockdown periods in 2020 are represented in gray shading (17 march to 11 may and 30 october to 15 december).

Figure 4 represents the weekly components of the model of Eq. (1) for the use of shared bikes in Toulouse for each year between 2019 and 2022. Similarly as for the hourly component within a day, these differ from the raw data of weekly use in that the weather and holidays effects of 2019 and 2020 are corrected, even though they account for less than 1% in the explained variance. As for the hourly usage, the year 2021 appears as a transitional period before returning in 2022 to a pattern very similar to 2019. A refined model allowing different weekly behaviors for working-days and weekends (i.e. with a component  $g(\text{week}, \text{type of day})$  instead of  $g(\text{week})$  in Eq. (1)) was tested. The additional parameters in this model were not statistically significant, which suggests that the weekly variations in BSS traffic on working-days and weekends were roughly proportional.

Figure 4 allows the comparison with two other types of urban transport, private cars and Public-Transport. Please note that for FCD data, all the urban territory is under consideration which contains the urban high-ways around the city. The first observation is that the summer period is clearly less impacted. Public transport's resilience to the pandemic is particularly bad since it remains largely underused until autumn 2020, with patterns for the weeks following the first lockdown which are similar to those during the second lockdown. The decrease is about 40% in 2020 compared to 2019, which is similar for example to observations in Shenzhen that show a decrease of 34% [RRMZ21]. With a latency of one month as for BSS, the road-traffic volumes (as represented by the observed fleet of vehicles in the available FCD data) return to stable levels (out of summer) better than those of Public-Transport and around 85% of the 2019 levels. The order highlighted

here regarding the impact of the pandemic on the three modes of transportation is consistent with previous findings [MiBSRK22].



## 5 Main spatio-temporal patterns of hourly BSS uses

In this section, we use Exploratory Factor Analysis (EFA) [Jolo2] to investigate the spatio-temporal effects of the pandemic on BSS usages. EFA is an unsupervised data compression technique that allows learning from data a small number of latent factors that meaningfully summarize the covariance matrix of the observed features (i.e., variables). In the model, the variables correspond to the  $p = 287$  dock-stations in Toulouse, for which we observe the amount of trips that begin at a given station in a given one-hour slot. Therefore, for each station, we have a total of  $q = 35087 = 24 \times (365 + 366 + 365 + 365)$  observations. Each one hour time slot represents a population sample point for which all variables are observed. Unlike the previous analysis in which we have distinguished among working-days, weekend-days or periods of the year on the basis of prior knowledge of relevant factors, we now assume to not have such preliminary knowledge, and thus aim to learn directly from the data the factors that can best explain existing similar temporal patterns between the different stations.

In the fundamental equation of the EFA model, observed variables are expressed as linear combinations of a given (fixed) number of unknown common factors, plus an additive term that can be considered as noise, or, in EFA terminology, as the uniqueness associated to each observed variable. Based on such principles, EFA fundamentally differs from Principal Component Analysis [DWD16] in the sense that factors are constructed by assuming that the covariance of the observed variables could be decomposed into two parts, i.e., a common and a unique one, while in PCA all the variance in the observed variables is analyzed and used for the determination of the components. Hence, EFA focuses on the interpretation of the relationships among the variables and on identifying the latent factors that explain such relationships as noisily observed in the data covariance matrix.

Following the usual EFA terminology, we call (*common*) *factors* the set of  $K$  latent “variables” that enters the construction of the observed variables and *factor loading matrix* the set of numerical relationships describing how much each factor explains each (observed) variable. The fundamental equation of factor analysis is

$$\mathbf{X} = \mathbf{\Lambda}\mathbf{F} + \mathbf{U}$$

where  $\mathbf{X}$  is the  $p$ -vector of observed variables,  $\mathbf{F}$  is the  $K$ -vector of unknown factors,  $\mathbf{\Lambda}$  is the unknown  $p \times K$  matrix of factor loadings and  $\mathbf{U}$  is the unknown  $p$ -vector of error variables (uniquenesses) associated to each of the  $p$  observed variable. Because of the normalization, the loadings can be interpreted as the correlations between the associated factor and the observed variables. More details on the EFA model, the solving procedure to compute factor loadings and uniquenesses, as well as approaches to select the number of  $K$  factors and to estimate factor scores can be found in the well-established literature on the subject [Mulo9, CL13, Jör78].

Factors extraction was performed using the Minimum Residuals (MINRES) approach [HJ66]. The working principle of MINRES is to minimize the sum of off-diagonal squared residuals of the correlation matrices of  $\mathbf{X}$ . An important design choice concerns the number of common factors that EFA should target. We rely on Parallel Analysis [Hor65], which uses the eigenvalues of the observations correlation matrix as rough estimates of the actual common factors. The presence of common factors shall induce large eigenvalues: the number of factors is set to the lowest rank above which all data eigenvalues are larger than those from the uncorrelated variables. Finally, once a set of factors is extracted, it is usual to perform a rotation in order to produce a more interpretable and simplified solution [Abd03]. Varimax rotation over BSS data worked best in that respect. It is an orthogonal rotation (which thus keeps factors uncorrelated) that maximizes the sum of the variance of the squared loadings.

In this study, Parallel Analysis yielded 23 factors sorted in decreasing order of explained variance. These account for 41.5% of the total variance, of which 82% is due to the first three factors. Lower-ranked factors are either restricted to a handful of stations or concentrated in a very small time period (e.g. a particular day). The following analysis has been performed using the departures data only. A similar one on the arrivals has been conducted, producing identical conclusions. Therefore, only the data from departures are presented to avoid redundancy.

The three main factors obtained from the EFA model, as well as the sixth factor, exhibit a strong periodic daily behavior that can be associated to a particular time of the day, as shown in Figures 5 and 7.

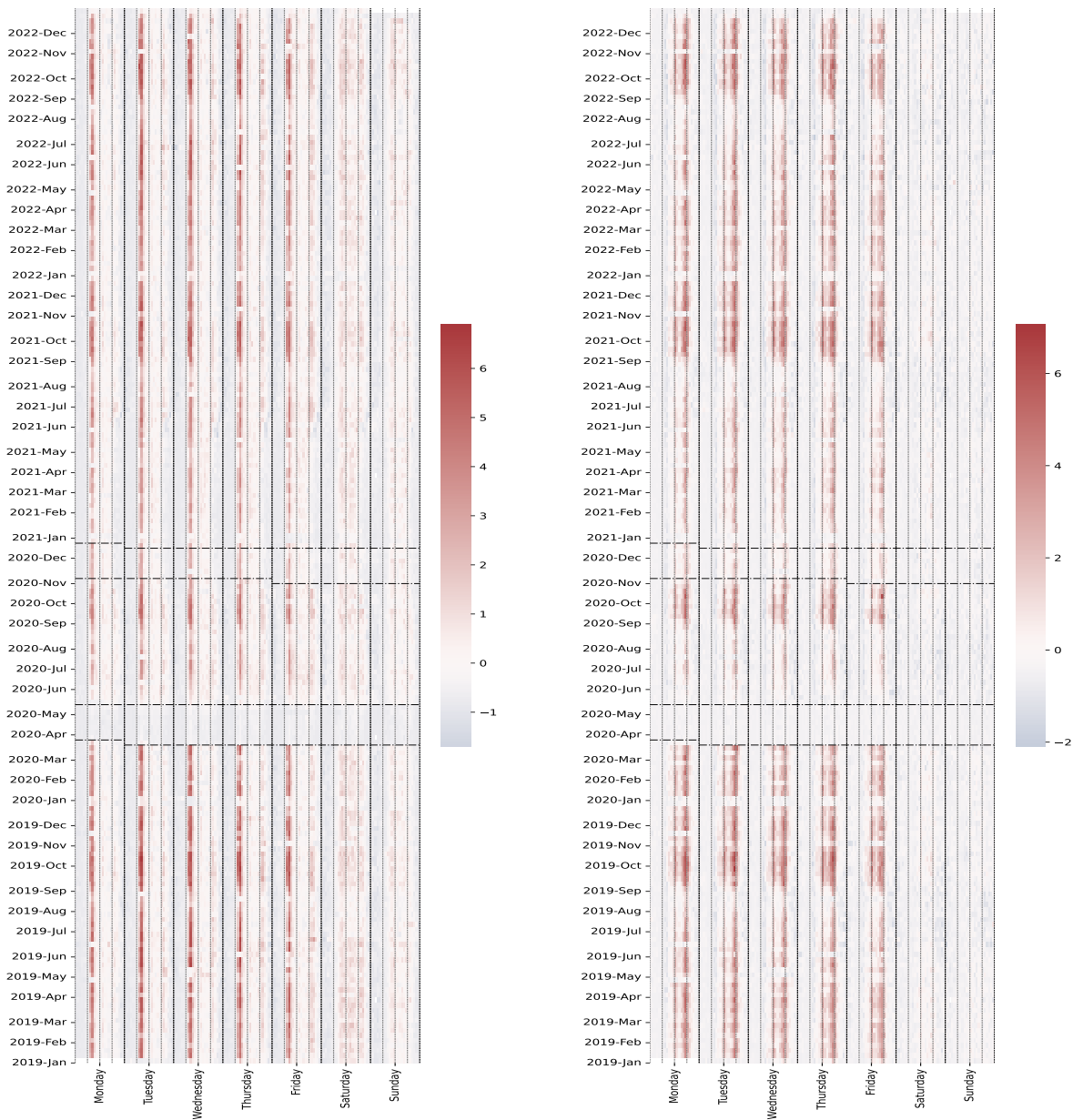


Figure 5: Visual representation of the first factor (left) representative of the morning peak activity, and the second factor (right) representative of the afternoon traffic, obtained from the ESA method. The horizontal axis displays the hourly values during one week, while the vertical axis stacks up the weeks of the four-year period considered.

The first factor, which accounts for around 14.4% of the total explained variance, displays a dominant morning peak for working-days during the four-year period with the sole exception of the first lockdown. It

is the only factor that shows significant scores for this morning peak and for a large number of stations, as seen in Figure 6. This factor is mainly associated with departures from residential areas. The second factor, which accounts for  $\approx 11.8\%$ , appears to be representative of the afternoon BSS use in relation to work places during the five working-days. Contrary to the morning peak, the afternoon traffic seems to have disappeared completely during the few months following the first lockdown. This phenomenon is less pronounced during the period following the second lockdown.

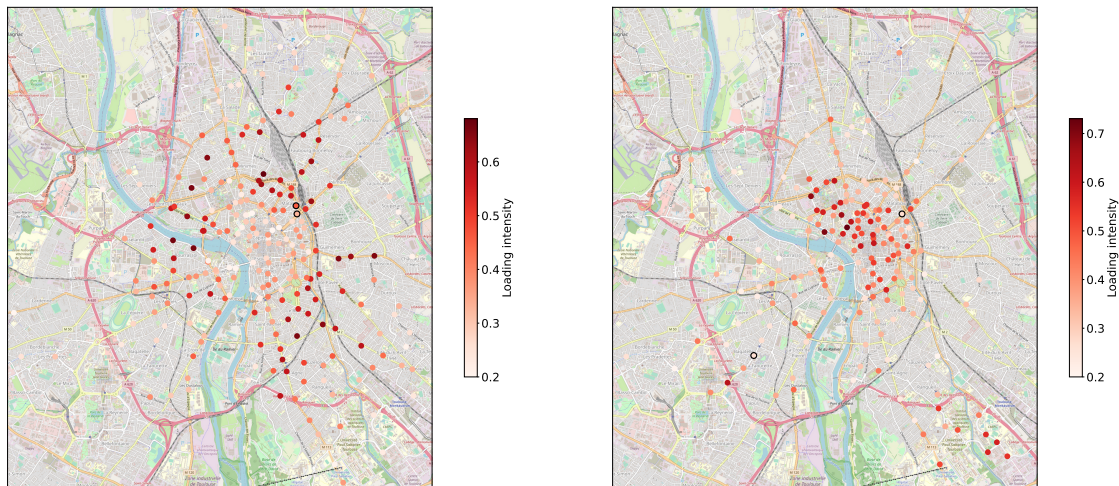


Figure 6: Geographical view of the loadings associated to the morning peak of the first factor (left) and the afternoon peak of the second factor (right).

The second factor corresponding to the afternoon traffic is the only one that scores positively for working-days and negatively for weekend-days. The high loadings are located almost exclusively in the city-center and the university areas, highlighting the traffic from people going back home from work.

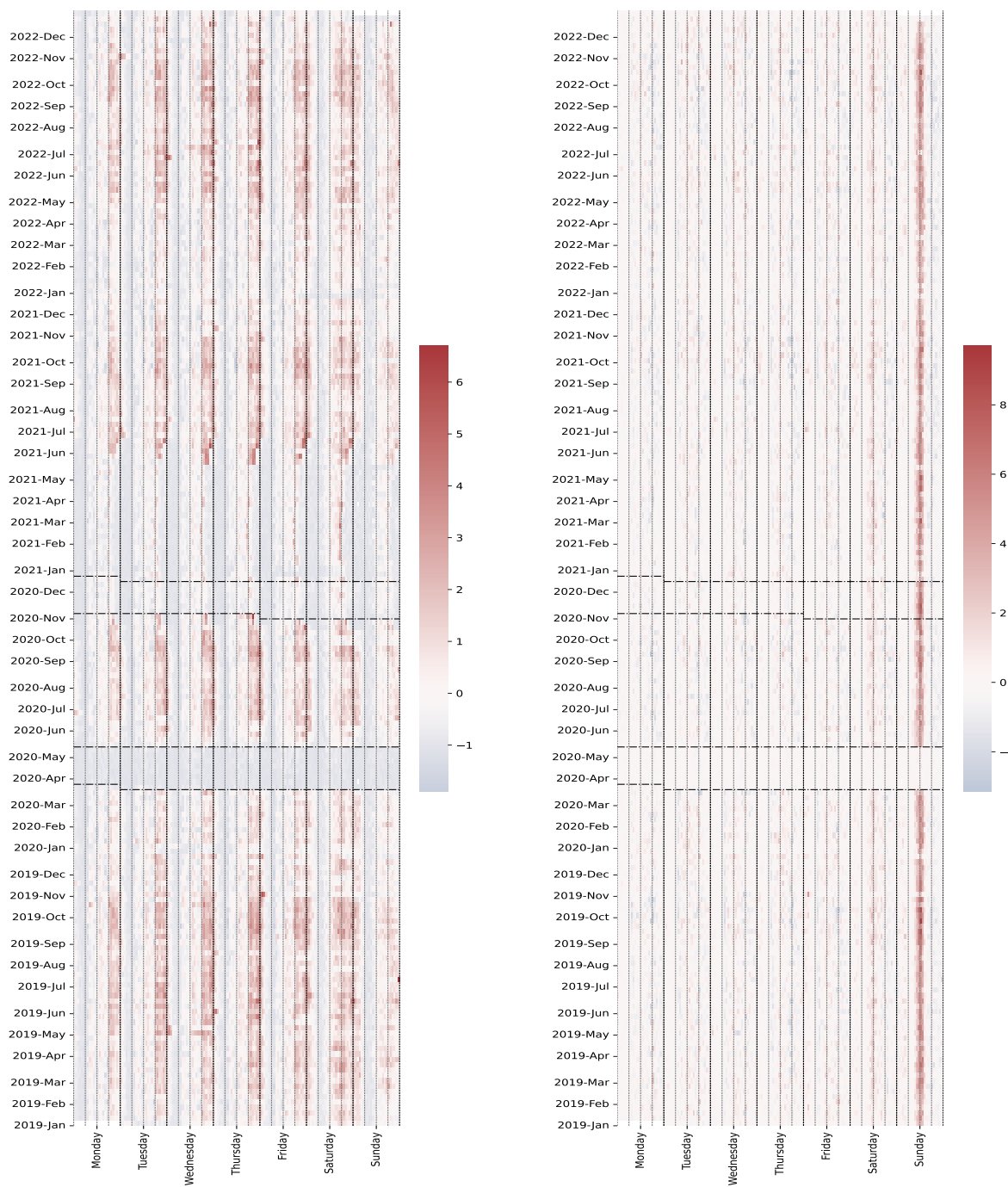


Figure 7: Visual representation of the third factor (left) highlighting the Toulouse night-life, and the sixth factor (right) mainly concentrated on Sundays around noon.

The third factor, visible in Figure 7 (left), is highly representative of the night-time activity in Toulouse. It shows daily peaks during the evenings and early nights, which are more pronounced in the middle of the week (say from Wednesday to Saturday) compared to the other days, while the loading map in Figure 8 pinpoints bike stations nearby areas with high concentration of bars, restaurants and other leisure activities such as the place du Capitole, place Saint Georges, place Esquirol or place Saint-Pierre. The curfew imposed between 9PM and 6AM starting from mid-october is clearly visible. In particular, for these last two weeks of October, we observe a peak of traffic between 8PM and 9PM, just before the curfew, probably due to people using bikes to come back home.

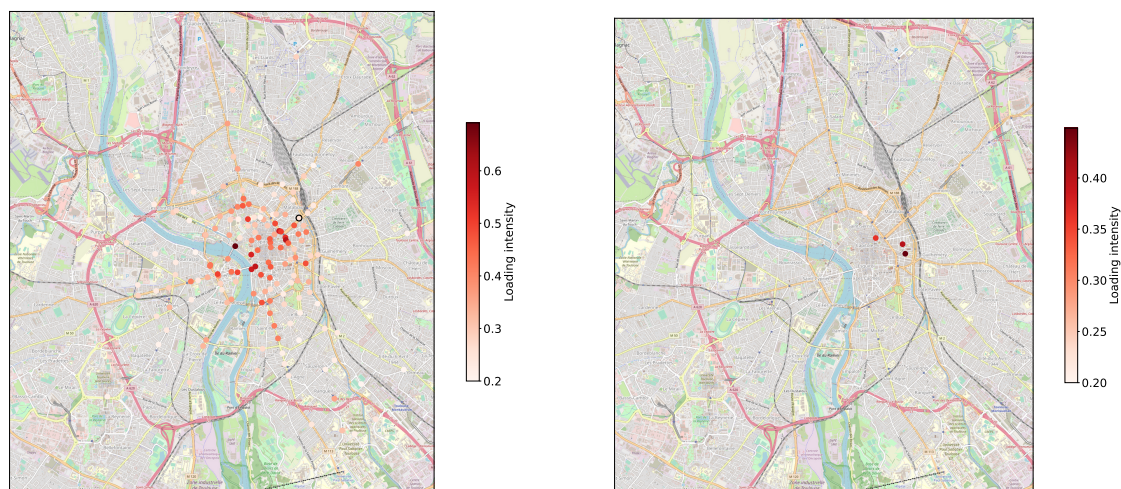


Figure 8: Geographical view of the loadings for the third factor (left) which depicts the Toulouse night-life, and the sixth factor (right) representative of the Sunday activity.

The sixth factor is concentrated in the three stations Saint Aubin Camichel, Victor Hugo and Colombette where the Sunday marketplace may explain the peak in activity in these locations. The marketplace was closed during the first lockdown but remained allowed during the second lockdown, as is clearly visible in Figure 7.

Finally, the fourth and fifth factors are concentrated in a few stations and reveal a change in activity during the considered period, due to e.g. renovations of the Matabiau train station that lasted until the end of 2021.



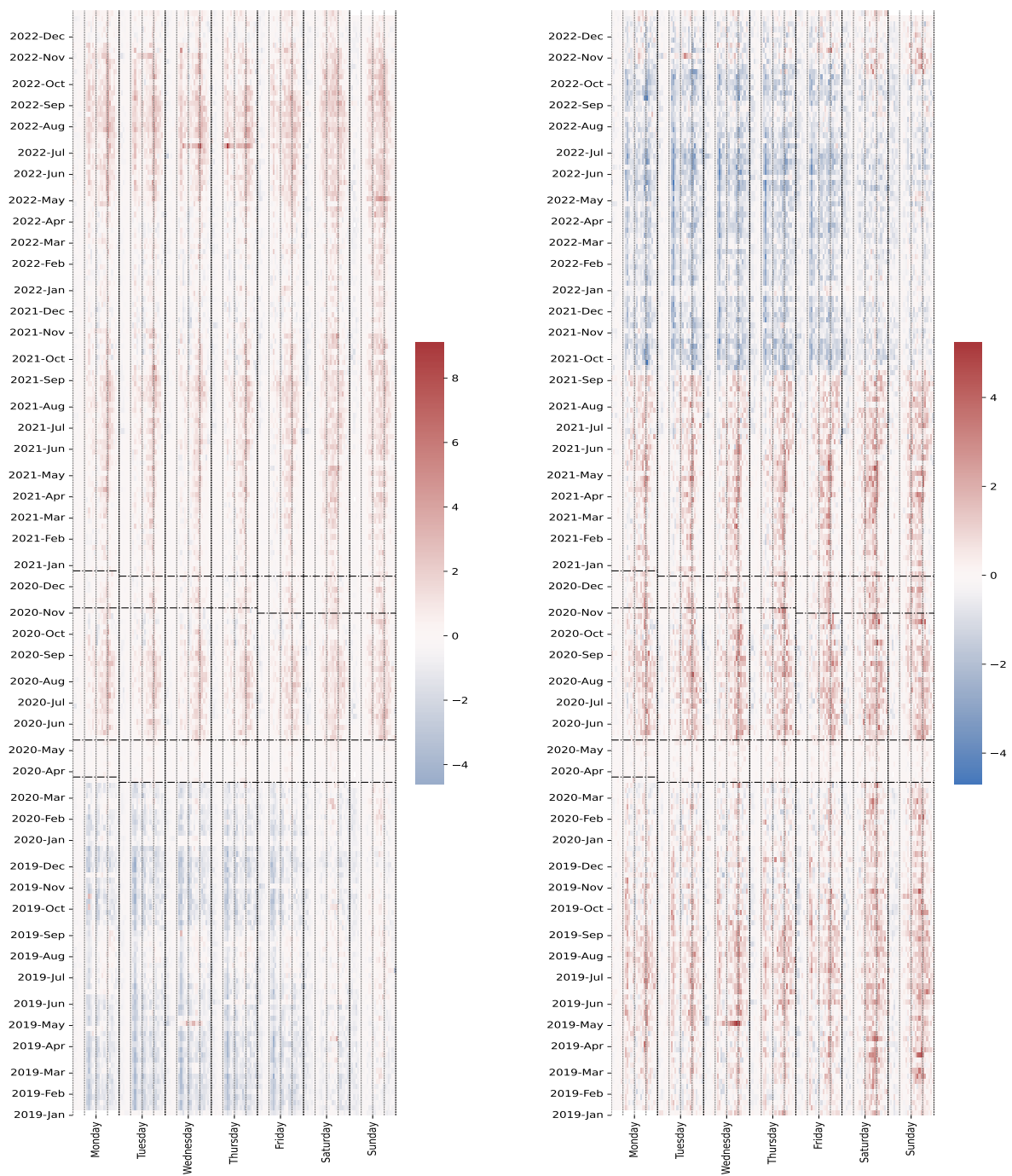


Figure 9: Visual representation of the fourth and fifth factors that can be associated with the Matabiau train station repairs that occurred during the first half of the period. A strong monotonic component is visible on both factors.

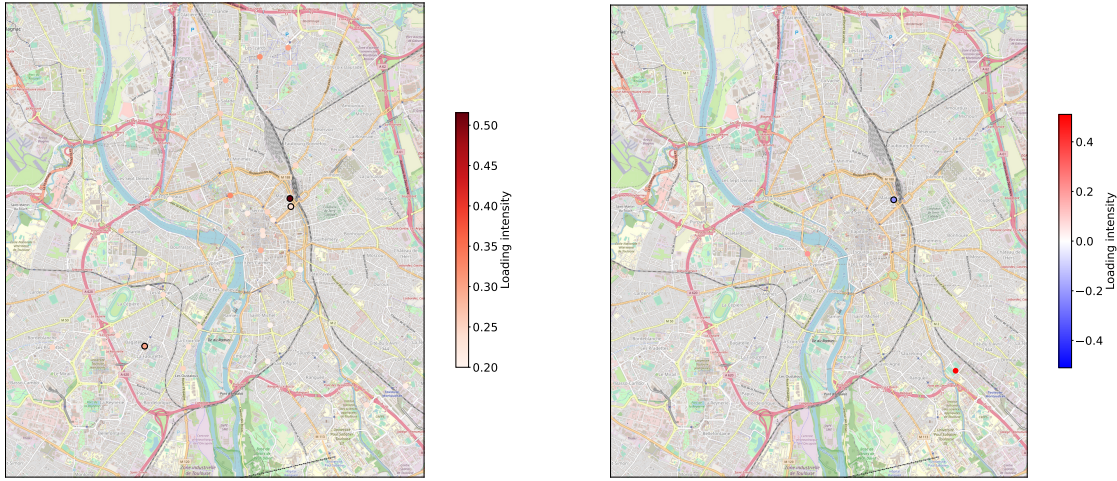


Figure 10: Geographical view of the the forth (left) and fifth (right) factor with a loading distribution concentrated in two or three stations, including Matabiau train station in both cases.

## 6 Conclusion

In this paper, we investigate the evolution of Bike-Sharing System (BSS) usages in Toulouse during the COVID-19 pandemic situation. Firstly, we compare the evolution of the amount of rental bikes during the four-year period between 2019 and 2022, with a 10-minutes time granularity. In this analysis, data from all the dock-stations have been aggregated, thus ignoring any spatial considerations. The results show that these time series can be very well explained as the product of two main effects: the annual tendency and the daily evolution. Our multiplicative regression model shows very good fitting scores, taking into account school-holidays and precipitations. Secondly, we use Exploratory Factor Analysis (EFA) to derive spatio-temporal patterns in the BSS usage over the four years. In the data, dock-station spatial granularity is preserved, thus permitting to observe and interpret, via the retrieved latent factors, the dynamics at the level of dock-stations instead of the entire network as in the first study. EFA highlights five and six latent variables, globally explaining around 50% of the variance.

Road traffic and Public-Transport were much more impacted than BSS. None of them appears to recover the pre-COVID level. After the first lockdown, with the same delay of about 1 month and until the second lockdown, with the exception of summer holidays, the road-traffic stabilizes at approximately 85% of the 2019 values for both towns. The traffic flow of public transport has the same dynamic in both cities, recovering a maximum of 60% of its value after the first lockdown and 75% of its value after summer holidays. This is consistent with previous findings in other cities. We found that trips duration significantly increased during the pandemic period for working-days but not for weekend-days where the reverse occurs.

The Explanatory Factor Analysis exhibited four strong periodic behaviors in BSS usage. The morning peak activity associated with departures from residential areas to work, appears as the main factor in the analysis, followed by the afternoon traffic present in areas with high density of business and activity centers

in a large portion of the Toulouse city center. The Toulouse night-time activity arises as the third stronger component of the analysis. Although the periodic nature of the time component, whether it concerns the daily, weekly or yearly evolution, are not included as preliminary knowledge in the EFA model, it does appear very distinctively in each factor and with high discrepancy from one factor to another. This shows the relevance of the methodology on this particular dataset.

Our results globally show that BSS appeared as a resilient mobility alternative during the pandemic situation. After a notable transitional year in 2021, BSS usage seemingly returned to the pre-pandemic standards in 2022.

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