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Impact of the COVID-19 pandemic on bike-sharing uses in two French towns: the cases of Lyon and Toulouse

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Abstract

Urban areas have been dramatically impacted by the sudden and fast 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 towns have shown that, in this context, cycling appears as a resilient, safe, and very reliable mobility option. Differences and similarities exist about how people reacted depending on the place being considered, and it is paramount to identify and understand such reactions in the aftermath of an event in order to successfully foster permanent changes. In this paper, we carry out two analyses, both from a geographical and temporal point of view: on the one hand, we compare the short-term effects of the pandemic on BSS usage in two French towns (Toulouse and Lyon), and on the other, hand we analyze its mid-term effects in Toulouse. We used Origin/Destination data for four years: 2019 (pre-pandemic), 2020 (pandemic before massive vaccination campaigns), 2021 (pandemic after massive vaccination campaigns), and 2022 (year after the pandemic peak). We consider two complementary quantitative approaches. Our results confirm that cycling increased during the pandemic, more significantly in Lyon than in Toulouse, with rush times remaining exactly the same for the four years, even during the lockdowns. The year 2021 shows a transitional profile between 2020 and 2022 that could be attributed to adaptation to living with COVID and perhaps also to the increased sense of safety brought by the vaccination campaign. We also found that trip duration during the pandemic situation was longer both on working days and weekends. Comparing BSS traffic with road traffic and public-transport validations shows that cycling is a resilient mode of transport in a pandemic. Among several general observations, we note that peripheral/city center BSS flow is more noticeable in Toulouse than in Lyon and that student BSS usage is more specific in Lyon.

1 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 identified case of COVID-19 in December 2019 in the city of Wuhan in China, measures have been taken worldwide and at different scales to stop the virus spread.

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 voluntarily chose to avoid using public transport, especially due to difficulties to comply with barrier measures when traveling. In this context, individuals have often re-evaluated their travel options towards more-isolated modes such as private cars, personal or shared bicycles [10, 15], and gender differences were observed [57, 37]. Considerations of health risks, travel flexibility, traffic reduction, or the desire to spend less money in times of economic crisis now shape individual decisions about transportation. More than two years after the peak of the pandemic, the eradication of COVID-19 and its variants remains uncertain in the short term and the emergence of new pandemics is a scenario now considered highly probable by the scientific community [21, 4]. If COVID-19 and its variants no longer constitutes a public health emergency of international concern, they are still present throughout the world and the efforts are now more focused on prevention, control and longer-term sustainable management of such a disease. 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 [2]. Observations have shown increasing usage of bikes during the pandemic in several urban areas all over the world [58, 29, 63, 71], proving that cycling can be a valuable choice, and, according to some, even contribute to faster economic recovery. In many cities, public authorities are implementing temporary facilities, strategies derived from “tactical” urban planning, to accompany this increase in cycling [19, 70]. Cycling is a largely flexible, inexpensive mode of urban transport easily adaptable to a wide range of situations, compared to, for example, public transport, whose adaptation is often a longer-term challenge [30].

In this paper, we propose a comparative analysis of spatio-temporal analysis of COVID-19 effect on BSS usage in Toulouse and Lyon (France) which were 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. We present an overview of the existing literature on bike sharing systems during the pandemic period in Section 2. After describing the data (Section 3), the following section (Section 4) provides general statistics and shows that the number of bikes leaving a dock-stations is accurately explained by a log-linear function of time variables and rain levels. 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 peak. Calculations and maps were made using R software and python language.

2 Bike sharing and the pandemic: a brief review

The effects of the COVID-19 pandemic on urban mobility have aligned with more gradual transformations that have been underway for several decades, resulting from the awareness of the ecological emergency [69]. These transformations tend to favor public transport and active or “soft” mobilities [8, 62]. 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 [84], and a relatively low cost deployment. On the other hand, its use may largely dependent on weather, topography, as well as on urban environment through speed moderation and bicycle facilities [9]. 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. In France, significant elements of the national cycling policy were launched just before the COVID pandemic: the bicycle plan in 2018 and the vote of the Mobility Orientation Law (“Loi d’Orientation des Mobilités”) in December 2019. These actions probably benefited from an acceleration of their implementations with the COVID19 pandemic [55]. These

policies are also 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 [11] in a noticeably different manner in urban center and suburban areas [82, 47]. Nevertheless, door-to-door trips are favoured when possible [28].

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 [61, 50, 14], taking advantage of a change in behavior during the health crisis, of a cognitive appropriation of cycling sometimes facilitated by the economic situation, to sustainably transform urban mobility practices and habits was 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 [24, 66, 33, 60]. For example, in the year following the introduction of BSS in the city of Lyon, a 44% increase in bicycle trips [16] 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 [52, 67]. 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 [24] and that BSS usages are related to bike usages as a whole [59]. 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 [67, 48, 25] and often with quite similar technological solutions. BSS appeared in France with a pioneer initiative in La Rochelle in 1976 [38] 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 [25, 77, 27, 49]. 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: about cities in the USA [79, 6], about New-York [76, 80, 58], Chicago [36], Lisbon [78], London [46], Seoul [73], Singapore [72], Zurich [45], Beijing [17, 68], Kosice Slovakia [43], or Valencia [65], but it is difficult to be exhaustive given the large number of published studies. Several other studies are based on online or on-site surveys in Tesseloniki in Greece [53], Seoul in South Korea [57], Lisbon [74] in Portugal, San Antonio in the USA [39], in several Italian towns [9], distributed in several European towns [12], or with participants from all over the world [10, 5, 18].

In recent papers [71, 75], the authors 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. The present paper is related to the first of these domains, focusing 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, [34] estimates the impact of the pandemic on both trip duration and number of trips in London. Confirming previous results (e.g., [46, 80]), the authors observe that trips are longer than expected during and after the spring 2020 lockdown. [71] uses an original graph theoretical approach for comparing flows of bikes during four 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. [58] also uses a graph theoretical approach on New-York BSS data showing the reconfiguration of BSS trips on Manhattan Island during the lockdown. [79] 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 Central Business District (CBD). Using weekly aggregated data for six cities in the

USA over a six month period, they confirm previous results that the distance to the CBD is positively correlated to BSS usage [26, 81, 54, 83] 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. The study reported in [36] 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 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.

To precisely evaluate the impact of the lockdown (and lockdown ease) on the BSS usage in London, [46] 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. [6] found that the effect was immediate, as soon as the first cases of COVID were reported, and reported a difference in BSS usage between weekdays and weekends. With a similar goal of analyzing traffic-bike change during the lockdown, [14] 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.

Our work is part of this series of papers which carry out quantitative analyses and which, for the moment, largely ignores the French cities. We distinguish two methods, with and without spatial considerations, to evaluate the impact of COVID 19 on both dimensions and at various scales. The spatio-temporal part of our study uses a method that allows to find specific dynamic patterns of dock-stations with no a priori assumptions, which was not used until now for this type of data.

3 Data description and context

In Lyon and Toulouse, a dock-based Bike-Sharing System (BSS) was installed by JC Decaux in 2005 and 2007 respectively. Since 20th February 2020, and progressively over the year, half of the Lyon fleet has been equipped with electric assistance which riders may choose to use or not. From our data, we have not been able to differentiate both types of users but we did not observe any significant increase in usage when electric assistance was implemented. So, we used the collection of all the Origin/Destination trips relative to JC Decaux BSS for both towns, without distinguishing electric or non-electric usage. We used data from 2019 and 2020 to compare the pandemic short-term effects for Toulouse and Lyon, and data from 2019 to 2022 to evaluate mid-term effects in Toulouse: 2019 (pre-pandemic), 2020 (pandemic before massive vaccination campaigns), 2021 (pandemic after massive vaccination campaigns) and 2022 (after-pandemic peak).

Each row of the dataset includes departure time and arrival time (with an accuracy to the minute), origin station and destination station (with geographical coordinates). The year 2019 will be considered as a “normal” year, as opposed to 2020 or 2021 when lockdowns have restricted mobility. For each year and each

town, a record of the dataset contains 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. These data accounted for between 2% and 4% of each dataset, with a large part of them being trips with identical origin and destination and of less than 1 minute. Hence, our input data are associated to real trips. Following these filters, the Toulouse data contain 284 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 (corresponding to a 23% decrease), 3.45 million in 2021 and 3.95 million in 2022. Lyon has 408 such dock-stations in 2019 and 424 in 2020, for respectively 8.11 and 6.96 million trips (14% decrease). As usual, the density of dock-stations is higher in city centers. Total population is about 1.37 higher in Lyon-Villeurbanne than in Toulouse (about 670 000 people against 490 000) for a number of BSS trips more than twice as high in Lyon. It reveals that the BSS network is better established in Lyon than in Toulouse, which is also revealed by the mean number of trips per bike which is about 50% higher in Lyon (2019 data).

Traffic changes between 2019 and 2020 are not homogeneous among the dock-stations: while city centers show a high decrease in uses, more periphery and residential dock-stations are less impacted and can even show some increasing usage Figure 1. These observations are consistent with the findings from [17, 36, 42] related to Beijing, Chicago and Seoul respectively, but inconsistent with those reported in [37] for Nanjing (China).

Dockless systems have emerged, but they are a complementary service to docked-BSS, with significantly different impact and users [48], and will not be discussed in this paper.

Public transport and traffic data were available for both 2019 and 2020, across both towns. The aim of this paper is not to delve into a detailed analysis of these datasets, but rather to give an insight of the pandemic's impact on various transportation dynamics, thereby facilitating a clearer interpretation of the results concerning BSS usage patterns. We used Floating Car Data (FCD) to evaluate traffic dynamics. The principle of FCD is to collect real-time traffic data by locating vehicles via mobile phones or GPS over the entire road network [3]. As for Public Transport data, the number of validations was provided on a per-15 minutes basis for the different networks (Bus, Tramway and Subway). Each validation corresponds to an entry of one traveller somewhere in the transport network. User data is anonymized so that each entry for the same user is assigned a different ID, making it impossible to reconstruct an individual user's daily usage patterns.

Weather observation data were provided by Météo-France for each hour. For each town, we considered data from the station closest to the city-center (Bron and Blagnac for respectively Lyon and Toulouse). The "rain level" variable has the highest negative correlation with BSS usages, which is consistent with previous findings [7]. Moreover, we observed strong correlations between several weather-related variables. Therefore, in the following we will just consider "rain level".

Both cities have similar dynamics in pandemic development with rates of intensive care hospitalization following the same pattern¹. After a peak at the end of March 2020, these rates were very low during the 3 summer months (June-July-August) and then rose again at the end of September to reach the peak of the second wave around November 10, 2020. Because of these similarities, data relative to COVID cases will not be taken into account in our analysis. We provide below a short timeline of the main dates of policy interventions in France relative to the pandemic situation.

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

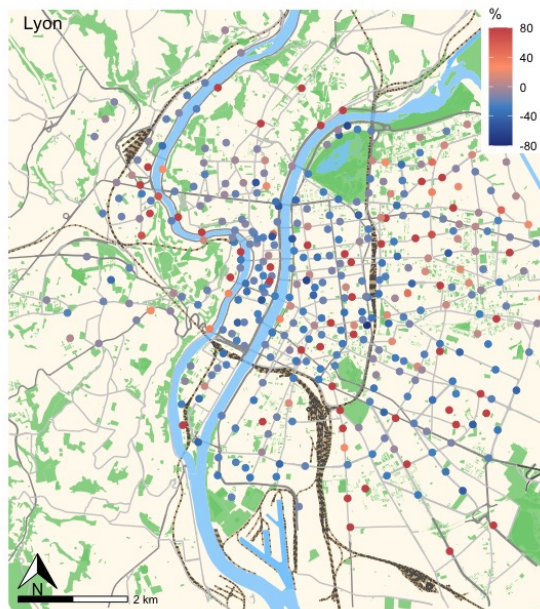
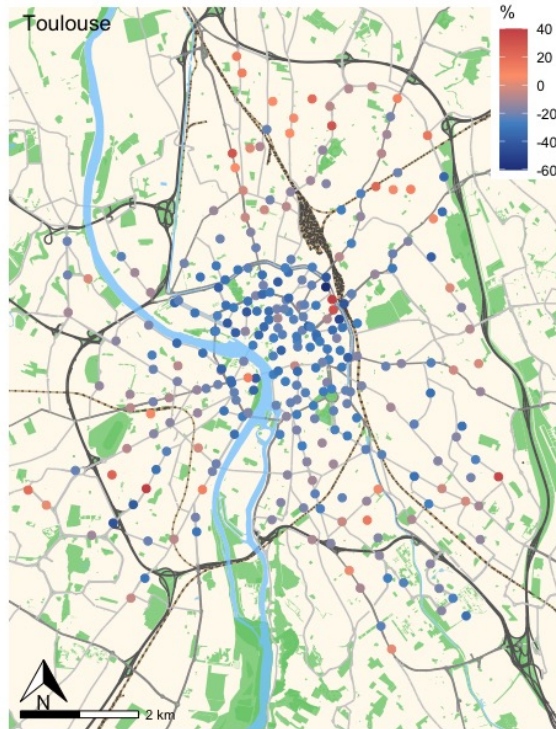
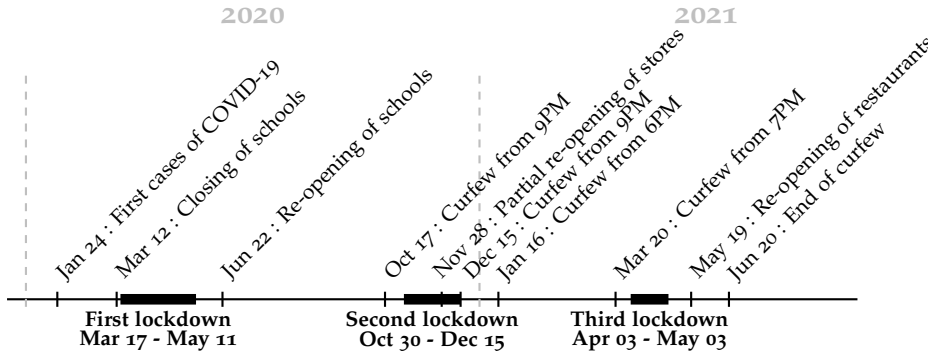


Figure 1: Locations of bike-sharing docks in Toulouse and Lyon. Each station is colored according to the percentage of traffic increase/decrease from 2019 to 2020. Only stations active over the two years are plotted.



4 Time modeling for citywide bike sharing use

For each city, BSS use is measured every 10 minutes over the course of the years 2019 and 2020 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 rain fall. The time component accounts for the time of the 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. Rain variable is divided into three levels according to the duration of rain fall 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 [36], is as follows

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

The functions f, g, h and ℓ are estimated non-parametrically via a linear model on the logarithm of BSS , with all variables treated as factors. The amount of precipitation only accounts for less than .5% of explained variance.

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 level of precipitation.

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-minutes-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 days of 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 .97 and .99 for the four considered years. 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 show the values of the function f of Eq. (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 biases. 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 below in Figure 4 as a weekly variation throughout the year.

Even if some differences exist, the distributions of daily BSS uses are extremely similar in 2019 and 2020 for working-days with a correlation of .989 in Lyon and .985 in Toulouse which quantifies the high resilience of travel daily rhythms during the pandemic. The perfect alignment of the 2019 and 2022 distributions shows that the BSS use daily rhythms for a working day has not been impacted at all by the pandemic, even if it took two years to go back to original. Policy restrictions for year 2021 were less severe than for 2020 but the end of the days were particularly impacted by the 3-month spring curfew. It can explain the gap between the 2021 distribution and the other distributions. To quantify the proximity of the different year distributions, we use the \mathbb{L}^1 distance between each pair of functions. For working-days, we measure a \mathbb{L}^1 distance of around .02 between the years 2019 and 2022 compared to .10 between 2019 and 2020 and .17 between 2019 and 2022. Similarly for weekend days, the \mathbb{L}^1 distance to the year 2019 preceding the pandemic is around .13 for 2020, .23 for 2021 while only .03 for 2022.

For working days, the four visible traffic peaks occur at the same time in Toulouse and Lyon for each year, namely around 8:45 AM, 12:15 PM, 1:45 PM and 6:15 PM, except for 2021 where the curfew at 6:00PM shifts the peak 15 minutes earlier. The cities show similar differences in behavior in 2020, with a small decrease in the 8:45 AM peak compensated by a higher and more spread-out use during late morning and the beginning of the afternoon compared to 2019. This change is amplified in 2021 with a BSS use more shifted to midday and afternoon, before going back to the pre-pandemic standard in 2022.

The decrease of BSS-use in the morning rush during the pandemic situation (year 2020) was observed in previous studies but often more pronounced [36, 14, 43, 45]. In these papers, the morning peak disappeared during the pandemic, contrary to what we observed even when focusing on the lockdowns (Figure 3). The relative increase in BSS use we observed around noon was also observed 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 previous studies. It may reflect different habits, or just the fact that these studies consider data with a one-hour accuracy, whose effect is to aggregate the two peaks. The use at night greatly decreased in 2020 in both Lyon and Toulouse, which can easily be explained by the curfews imposed by the French government.

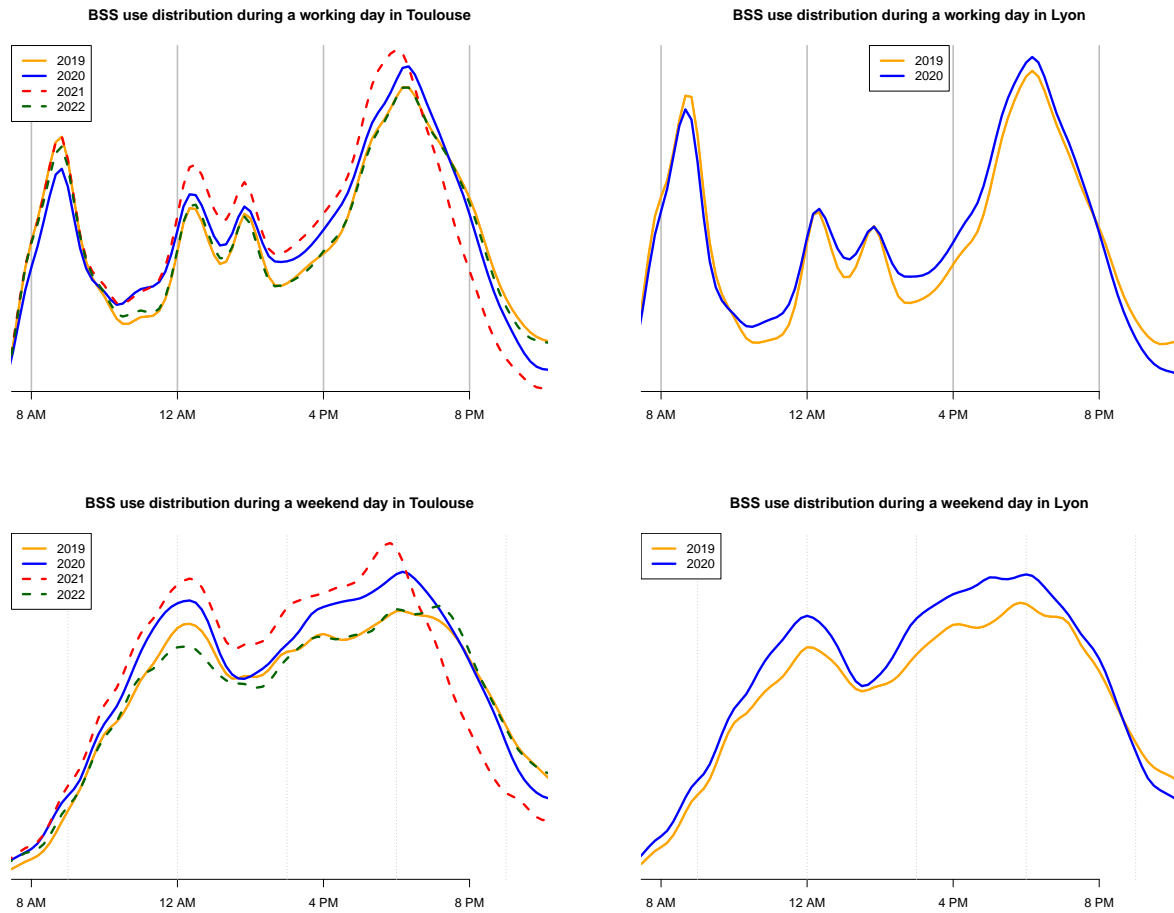


Figure 2: Mean BSS use distribution over the course of a working-day and weekend-day in Toulouse and Lyon, as fitted by the model. Curves are normalized so that the total sum of uses over the year is equal to 1 for each curve.

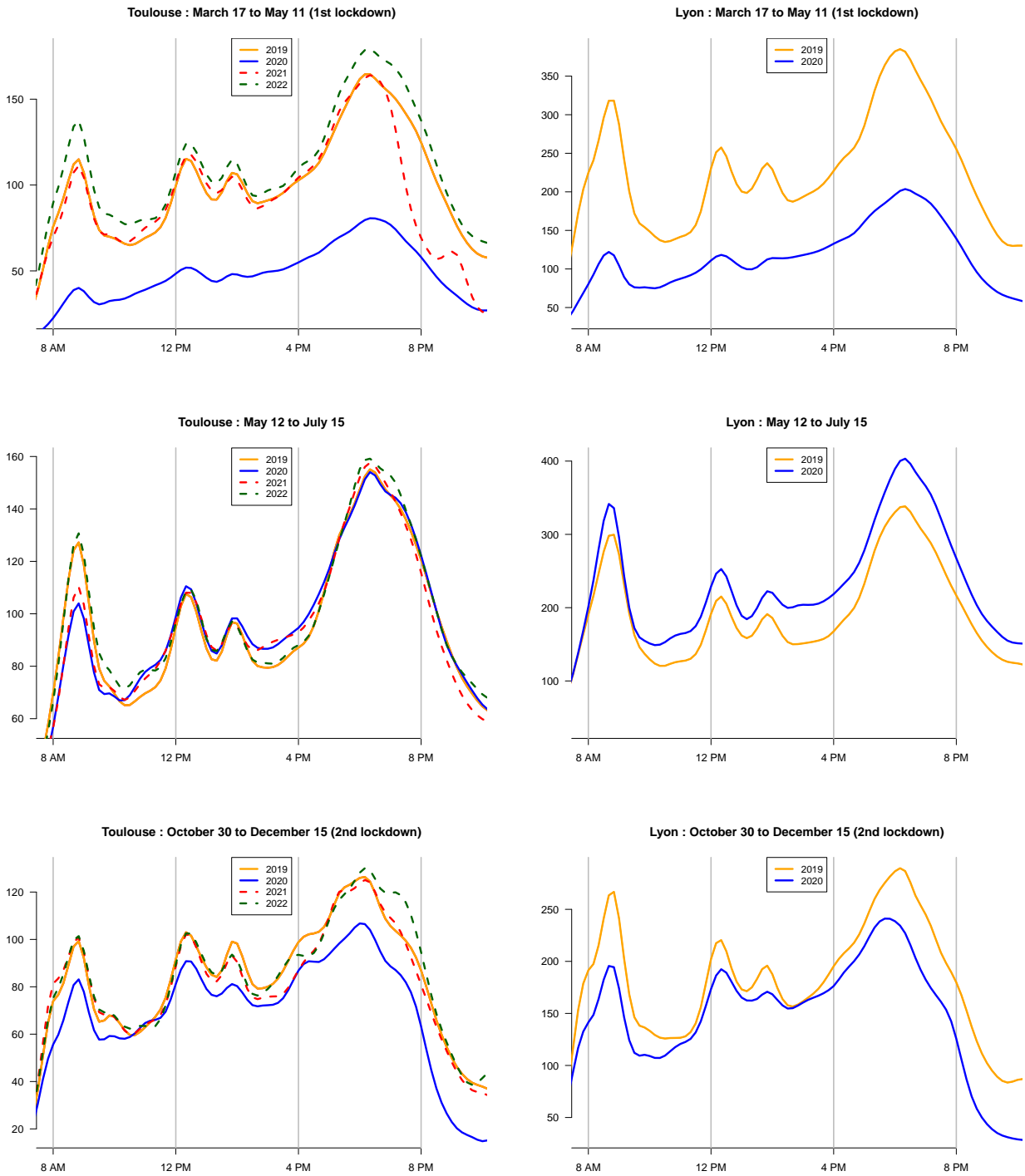


Figure 3: Comparison of the average BSS use during a working-day for the two 2020 lockdowns and just after the first lockdown.

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. Top plots shows that the heavy restrictions of the first lockdown in France almost completely obliterated the BSS use. Nevertheless, the four peaks are still discernible and occur at the exact same times. The impact of the second lockdown (bottom plots) was much less noticeable than the first one with a similar day pattern as usual and only a moderate decrease in volume. For both towns, it is interesting to notice that the morning peak for working-days is preceded by an inflection point around 8:00 AM. It reveals a bimodal distribution which probably deserves to be studied in more detail.

The weeks following the 1st lockdown (middle plots in Figure 3) reveal different BSS uses in the two towns. In Lyon, the slight morning peak decrease is more than balanced by a late morning and early-afternoon spread-out. It is also worthwhile noticing that, right after lockdown, the evening peak recovered its 2019 level which shows how resilient BSS usage is. In Toulouse, the observed pattern is different, with a volume of usage which does not get back to its pre-pandemic level. The almost-halved morning peak is strongly impacted and this is not balanced by the rest of the day with the three other peaks also largely diminished while inter-peak periods recovered their 2019 level. Under the hypothesis that working from home was equally distributed in Lyon and Toulouse, it suggests that BSS is more resilient in Lyon than in Toulouse for commuting. This may also be partly due to the higher number of coronapists installed in Lyon (76km) than in Toulouse (12km). This effect would confirm previous results [56, 14].

On weekend-days, rhythms in Lyon and Toulouse are also very similar with more variability in 2020 between the two peaks and a drop in usage around 1:30 PM. The presence of two peaks was observed in [64] but not in [45], [31] or [14] where continuous increase in usage from noon to the end of the afternoon is probably due to data aggregation. The afternoon peak occurs slightly later compared to the highest congestion hours in these cities, situated around 5:45 PM.

We also observe a peak of traffic bike around 0:30 AM in 2019, on weekends, especially for Lyon (outside the range shown in our plot). In our Public Transport data for Lyon, it coincides with a peak of underground exits (preceded by a high number of entries just before and around midnight). It illustrates the importance of BSS/underground inter-modality, which is mainly asymmetric (BSS followed by the underground, or the other way round depending on the time of the day).

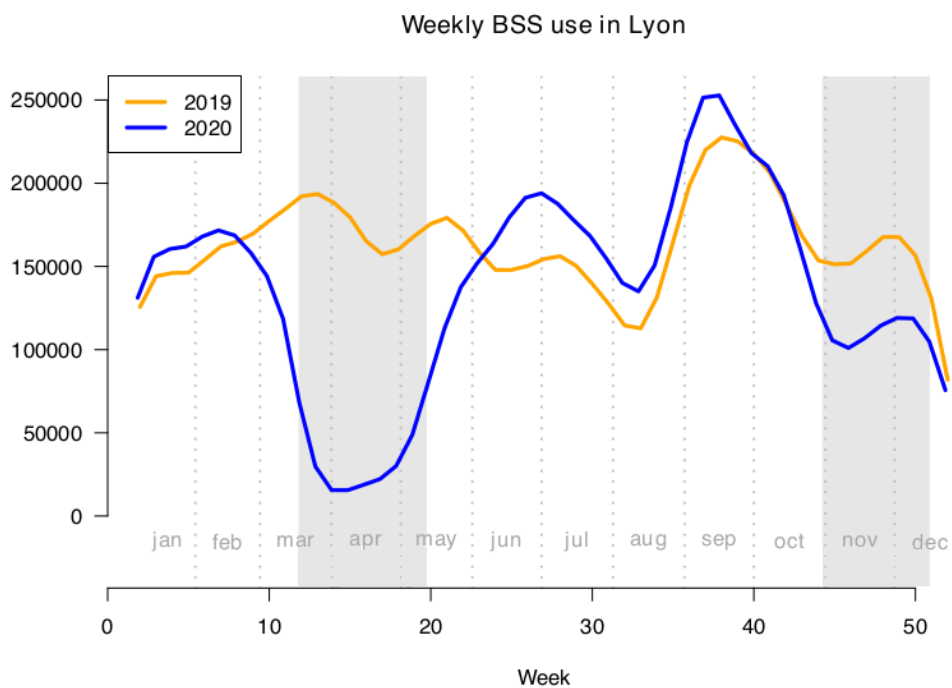
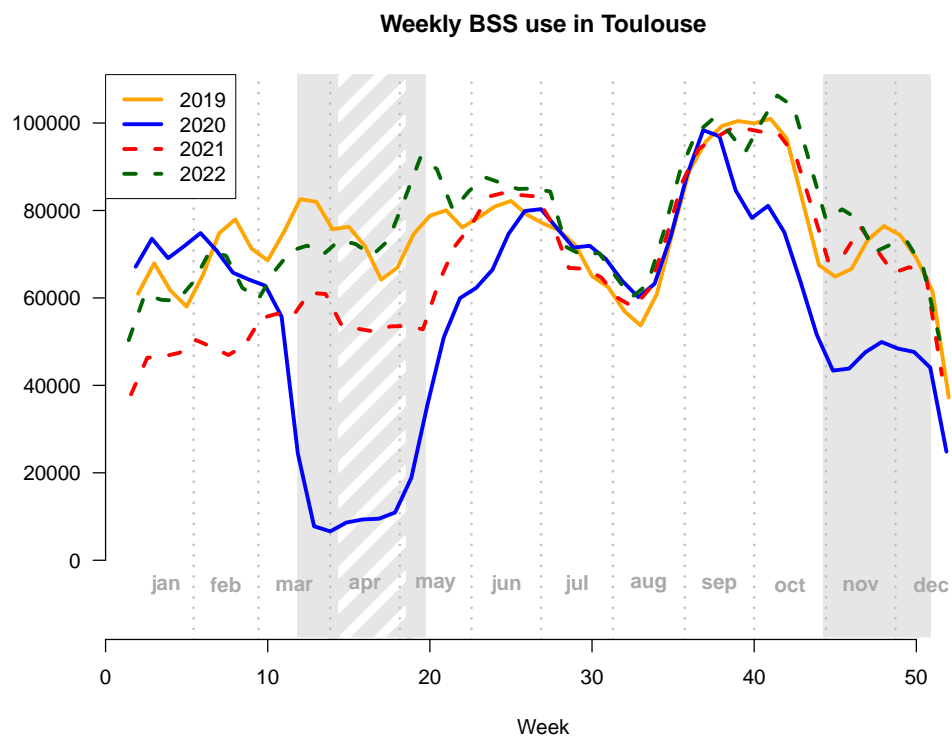


Figure 4: Weekly evolution of BSS use over the course of each year in Toulouse and Lyon, as provided by the model. Curves are normalized so that the total sum of use over the year is equal to the observed value for each curve. The lockdown periods in 2020 are represented by gray areas (17 March to 11 May and 30 October to 15 December) and the 2021 lockdown is in hatched white.

Figure 4 (top) represents the weekly components of the model of Eq. (1) for each year. As for the daily component, these differ from the raw data of weekly use in that the weather and holidays effects are corrected, even though they account for little in the explained variance. The areas under the curves are not normalized, so the y-values can be considered as a good estimator of the BSS traffic. For the pre-pandemic year (2019), Toulouse and Lyon curves have the same profile, characterized by a low number of trips during summer holidays followed by a higher number between mid-September and mid-October. The difference between the two extremes varies from nearly one to two in both towns. The end of the year, when many people take vacations, is a second period of low use in both towns. These simple observations show that shared bikes are largely used for working activities, which is reinforced by the magnitude of the morning and evening peaks in Figure 2. 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.

For 2020, corresponding to the peak of the pandemic and before the massive vaccine campaign, rhythms are still similar for both towns. The number of trips is largely reduced during the lockdowns and the ratio between Lyon and Toulouse remains the same as outside the lockdowns with approximately twice as many trips in Lyon. Less strict than the first one (schools remained open and many sectors were able to continue their activity, even if universities switched to online courses), the effect of the 2nd lockdown is lower. An interesting period is the weeks after the first lockdown. Very quickly, in 2 weeks for Lyon and 4 for Toulouse, the number of bike trips exceeds the 2019 levels. The jump in BSS usage observed right after the first lockdown is consistent with previous results for western cities ([10, 79, 80]). The difference in the amount of time required to get back to the level of the year 2019 after the 1st lockdown in the two towns is due to the decrease of BSS use in 2019 in Lyon in the period between mid-May and mid-June. It corresponds to a special event when, within 2 weeks, a large part of the BSS-bike fleet was stolen. Without this decrease, the amount of time required to get back to the level of 2019 would have been similar in both towns and approximately equal to 1 month. This is similar to what [17] was observed in Beijing but twice shorter than in Brooklyn [80] and in Chicago [36].

Year 2021 appears as a transitional period before returning in 2022 to a pattern very similar to 2019. The third lockdown had minimal impact, with the recovery time to pre-pandemic levels being halved to just two weeks. This quicker recovery could be attributed to people adapting to living with COVID-19, as well as the increased sense of safety stemming from the vaccination campaign. A return to normalcy in habits is observed. Additionally, there's a notable increase in BSS users in 2022 compared to 2019, though it remains challenging to determine whether this rise is the outcome of a long-term trend towards ecological awareness or a direct effect of the pandemic.

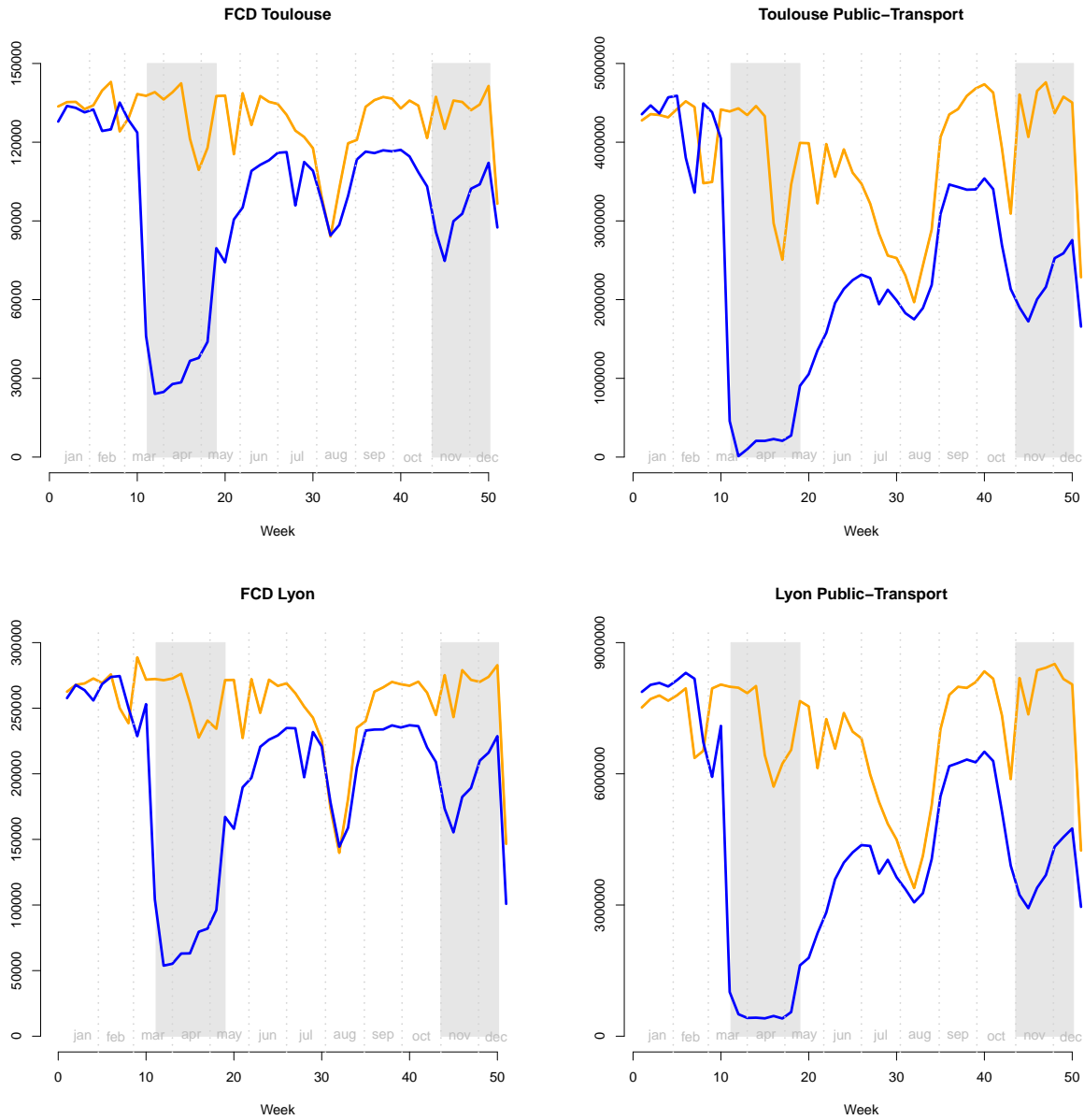


Figure 5: Weekly evolution of road traffic (FCD data) and Public-Transport entries for 2019 (orange) and 2020 (blue), plotted from the raw data.

Figure 5 allows a comparison with two other types of urban transport, private cars and Public-Transport. For FCD data, all the urban territory is under consideration, including urban highways around the cities. The first observation is that patterns are very similar in both towns. Neither

Public-Transport nor road-traffic recovered in 2020 their 2019 levels. The summer period is clearly less impacted in both towns. Public transport's resilience to the pandemic was particularly poor since it remained largely underused until autumn 2020, with patterns for the weeks following the first lockdown which are similar to those during the second lockdown. In both towns, the decrease is about 40%, as compared to 2019, which is similar to observations in Shenzhen showing a decrease of 34% [62]. With a latency of one month as for BSS, road-traffic volumes (as represented by the observed fleet of vehicles in the available FCD data) return to stable levels (outside summer) better than those of Public-Transport and reach around 85% of the 2019 levels for both towns. The order highlighted here regarding the impact of the pandemic on the three modes of transportation is consistent with previous findings [12].

Consistent with previous findings [45, 76, 36, 62], BSS trip duration increased for commuting during the pandemic situation, as pictured in Figure 6. We observe the same phenomenon as previously for other distribution with trip durations returning in 2022 to their 2019 standards, with a transitional year of 2021. Distributions are highly skewed due to the presence of a few long (more than 2 hours) trips, not visible in the boxplots. An analysis of variance has been conducted on trip duration trimmed of values below one minute and above two hours in order to handle the outliers and skewness. It shows that the differences in trip duration between 2019 and 2020 are highly significant for working-days on the first four periods but becomes less visible in the second lockdown (p-value $\approx .011$).

About weekends, Lyon and Toulouse shows similar situations with an increasing of trip durations. These results are consistent with previous findings (eg. [45]).

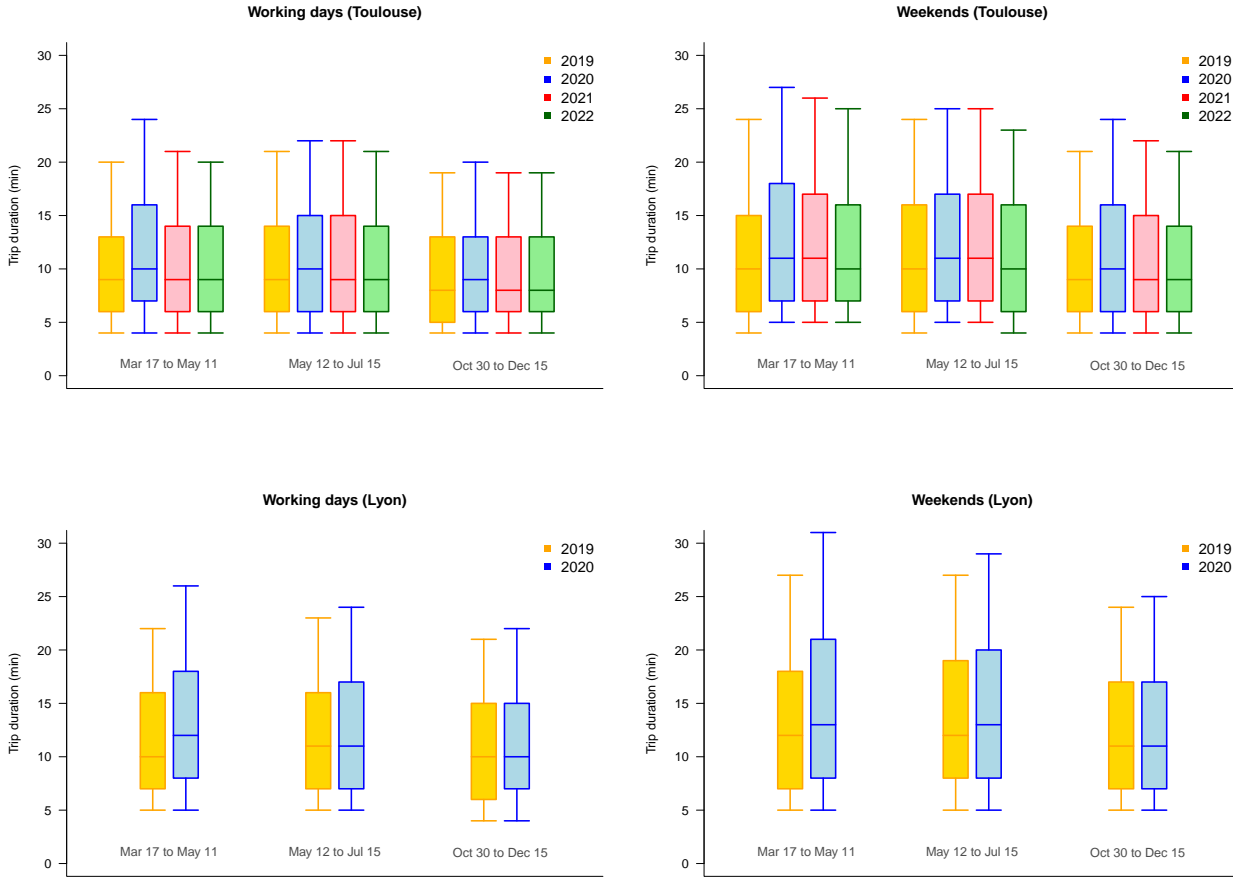


Figure 6: Comparison of trips duration over the different time periods for Lyon and Toulouse merged data. First (Q_1), second (Q_2 , median) and third (Q_3) quartiles are plotted. The boundaries of the whiskers are the 10^{th} and 90^{th} percentiles.

5 Main spatio-temporal patterns of hourly BSS use

In this section, we used Exploratory Factor Analysis (EFA) [40] to investigate the spatio-temporal effects of the pandemic on BSS usage. EFA is an unsupervised data compression technique that allows extracting from data a small number of latent factors that meaningfully summarize the covariance matrix of the observed features (i.e., variables).

We chose to extract three distinct EFA models from the available datasets: one for Toulouse (T_1) and one for Lyon (L), covering the two years 2019 and 2020, and one for Toulouse (T_2) covering the four years from 2019 to 2022. The observed variables correspond to the $p = 284$

(resp. $p = 424$) dock-stations in Toulouse (resp. Lyon), for which we observe the number of trips which begin at a given station in a given one-hour slot. Therefore, for each station, we have a total of $q = 17544 = 24 \times (365 + 366)$ observations for the two first models and $q = 35087 = 24 \times (365 + 366 + 365 + 365)$ observations for the third one. Each one-hour time slot represents a population sample point for which all variables are observed. Unlike our previous analysis in which we distinguished between working-days, weekend-days or periods of the year on the basis of prior knowledge of relevant factors, we now assume that we do 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. Focusing on models T1 and L for the two years 2019 and 2020 allows to highlight the main factors of stability and changing between the pre-pandemic and the pandemic situations. When we consider the model T2 for the four years from 2019 to 2022, we rather favour the mid-term effect of the pandemic by identifying factors that cross the pandemic year without significant effects and others that have a meaningful effect.

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 [23] 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 one and a unique one, while in PCA all 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 enter 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 (uniqueness) associated to each of the p observed variables. Because of normalization, the loadings can be interpreted as the correlations between the associated factor and the observed variables (the BSS stations in our case).

More details on the EFA model, the solving procedure to compute factor loadings and uniqueness, 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 [51, 22, 41].

Factor extraction was performed using the Minimum Residuals (MINRES) approach [32]. The working principle of MINRES is to minimize the sum of off-diagonal squared residuals of the correlation matrices of \mathbf{X} . Unlike maximum likelihood estimation [44], MINRES does not rely on any assumption about the distribution of observed variables and can produce valid solutions even when applied to singular matrices [41, 13]. An important design choice concerns the number of common factors that EFA should target. We rely on Parallel Analysis [35], 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 [1]. Varimax rotation over BSS data worked best in that respect. It is an orthogonal rotation (which thus keeps factors uncorrelated) which maximizes the sum of the variance of the squared loadings.

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. As previously discussed in relation to factor scores, time series have been centered and scaled during the factor analysis process, which means that the comparisons between stations is based on their pace and not their absolute intensity.

In this study Parallel Analysis yielded 23 (resp. 27) factors for Toulouse (resp. Lyon) sorted in decreasing order of explained variance. Regarding the cumulative variance explained by these factors, 82% is due to the first three factors for Toulouse (T1 and T2 models) and the first four for Lyon. For both cities, the 5th and the 6th factors are of special interest by their particular spatio-temporal distribution. For both cities, the cumulative explained variance by these 6 factors is about 90%. Other lower-ranked factors are either restricted to a handful of stations or concentrated in a very small time period (e.g. a particular day or a timeslot). The 3rd factor in Lyon and the 4th factor in Toulouse (for both models T1 and T2) are representative of the new bike stations installed by end of 2019 / beginning of 2020, and will not be discussed here.

In the loading maps, except for Figure 11, only stations with loadings greater than .3 are plotted. We have chosen the plots that are the most representative and additional figures can be found in supplementary materials.

5.1 The commuting peaks and the role of students

The first factor, which accounts for around 14% (resp. 22%) of the total explained variance for both Toulouse models (resp. Lyon), points out the dominant morning peak for working-days with the sole exception of the first lockdown (Figure 7). Second and third lockdowns show little effects on this commuting peak. It is the only factor that shows significant scores for this morning peak and for a large number of stations. This factor is mainly associated with departures from residential areas. This phenomenon is particularly observable in the city of Toulouse where residential areas are more clearly separated from business districts and activity centers (see also Figure 1). Loadings for the city of Lyon appear to be lower in the most touristic zones, such as the "Presqu'île", and in La Doua university district. This can be explained by considering that such locations have very particular traffic patterns at this time of the day. It is worth noticing that, in the city of Lyon, the first factor also shows low but significant positive scores for the end-of-afternoon peak, which is not the case for Toulouse. This can be again explained in terms of the urban fabric associated to the corresponding areas of the city of Lyon, which are characterized by a more mixed residential-work land use than in Toulouse. As a consequence, dock stations in these zones show some non-negligible activity (bike trip departures) also at the end of the afternoon, probably due to people leaving their work places at the end of the day.

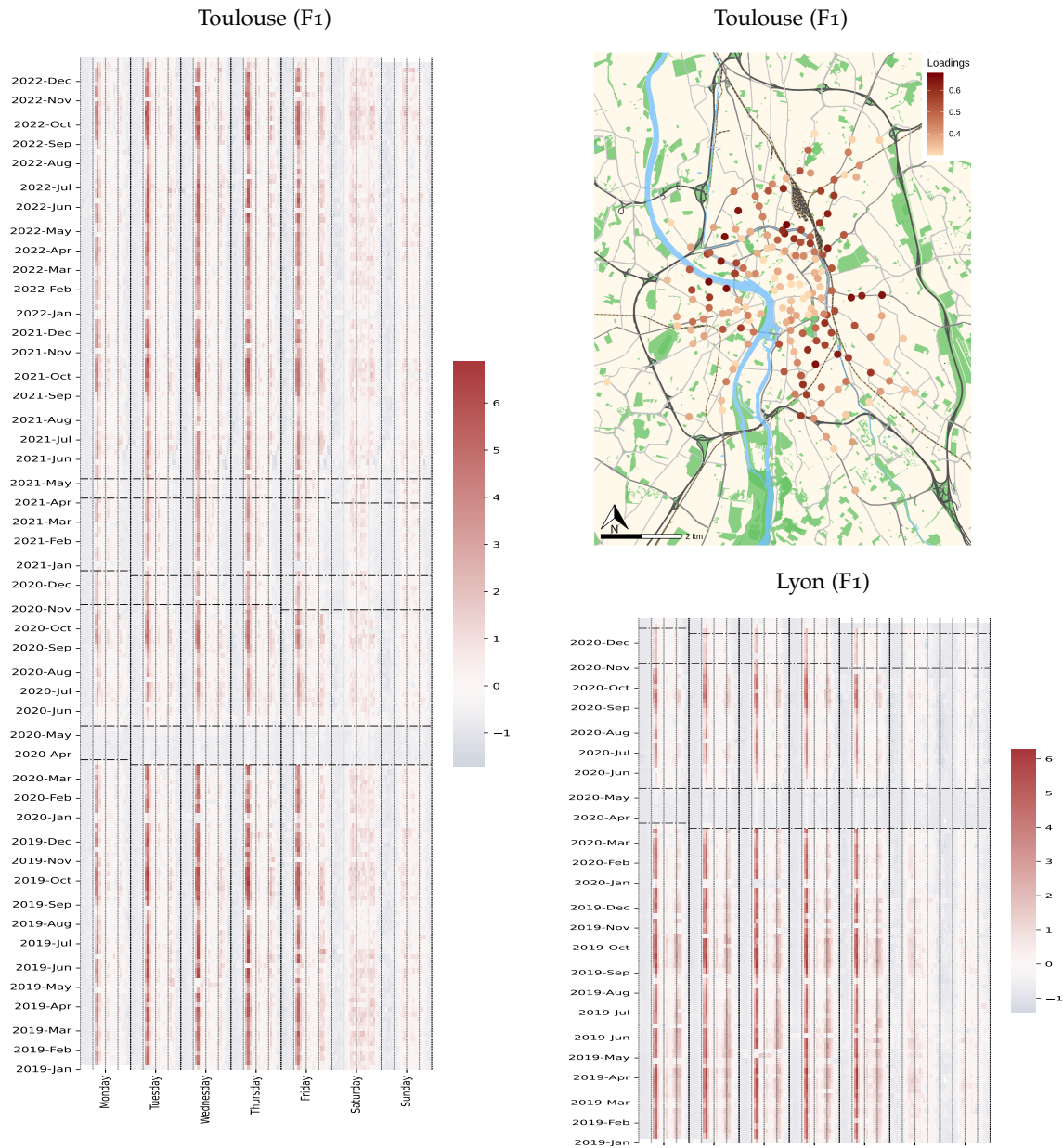
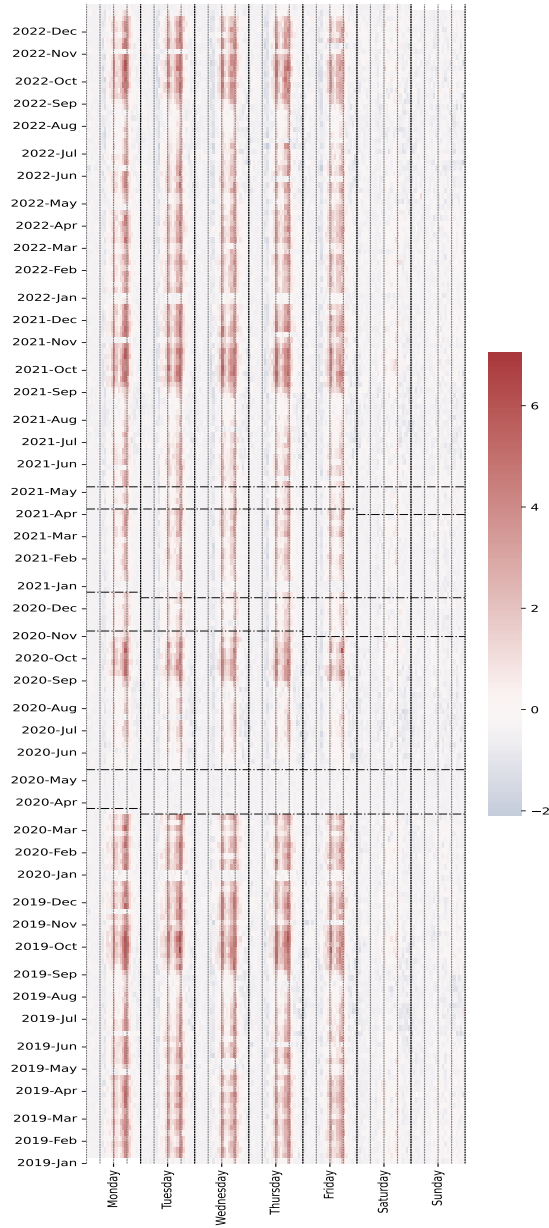
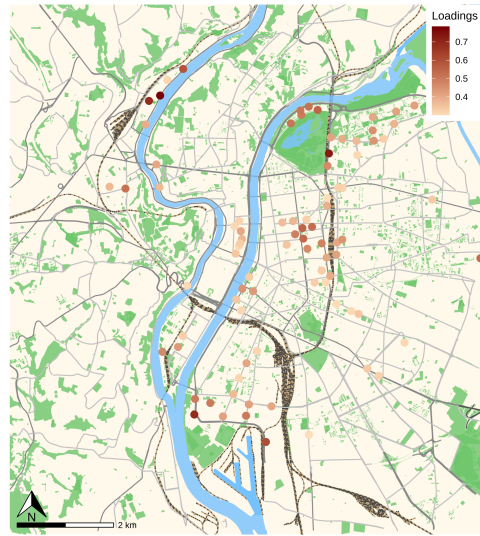


Figure 7: Hourly representation of the first factor scores of the morning peak activity obtained from the EFA method for Toulouse T2 (left) and Lyon (right). Lockdown periods are delimited by dotted lines. The horizontal axis displays the hourly values during one week, while the vertical axis stacks up the weeks. Results for the two-year model T1 are similar to those of the four-year model T2. Top right plot is the loading map of the departure BSS traffic associated to this first factor in Toulouse (the average loading intensity appears in color for each dock-station).

Toulouse (F2)



Lyon (F4)



Lyon (F4)

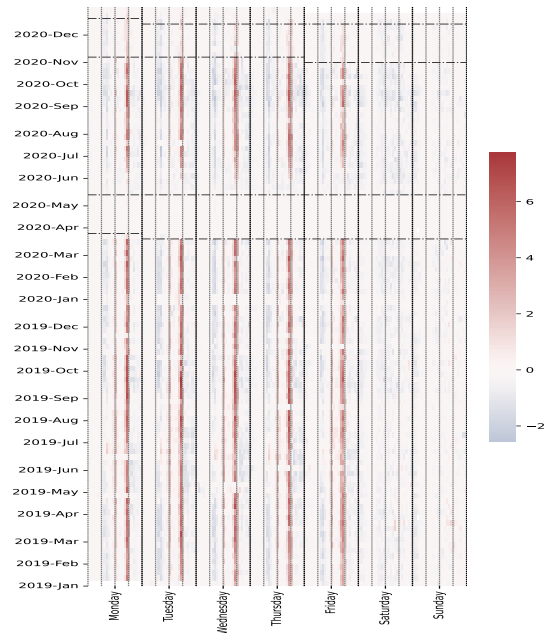


Figure 8: Hourly representation of end-of-afternoon commuting peak highlighted by the second EFA factor for Toulouse and fourth EFA factor for Lyon. (Top right) Loading map of the departure BSS traffic associated to the peak in Lyon.

The second factor for Toulouse and the fourth for Lyon, which respectively accounts for around

12% in Toulouse and 6% in Lyon, are the only factors that count positively for working-days (days with a positive score sum) and negatively for weekend-days (days with a negative score sum). So, they are clearly related to commuting and, more precisely, to the end-of-afternoon BSS journey from work to home (Figure 8). The effect of the pandemic during the lockdowns is decreasing, from the first lockdown to the third one. Several differences can be highlighted between the two towns. First of all, as one of the effects of the COVID-19 pandemic, the end-of-afternoon traffic peak in 2020 took longer to get back to pre-pandemic levels in Toulouse than in Lyon. Comparisons with university holidays, and the high activity of dock-stations located near the universities for this factor, appear to confirm the fact that student usage plays a fundamental role in this Toulouse BSS factor profile. It is not the case for Lyon where university student BSS usage is mainly represented by the fifth factor (Figure 9). Indeed, the loading map corresponding to this fifth factor for Lyon is perfectly associated to university campuses, and university holidays or online courses restriction period due to the COVID pandemic. This fifth factor for Lyon count for 1.6% of the total variance which is relatively low, and, even if we add the values of the variances of the fourth and fifth factors, the result is low. So, either the relative importance of students in the BSS use in Lyon is lower than in Toulouse, or this use is more spread over all the other factors.

Secondly, we noticed that this end-of-afternoon factor is more concentrated, both in time and space, for the city of Lyon. Stations concerned by factor 4 for Lyon are in fact located in the main work places of the city, while the whole city-center (plus the university campuses) is concerned by the second factor in Toulouse. This is a general consideration unrelated to COVID that can be explained again in terms of the different fabric of the two cities and the fact that the end-of-afternoon peak related to business activities is already partially represented by factor one for Lyon, together with the morning peak, for stations belonging to areas with a more mixed residential-work behaviors.

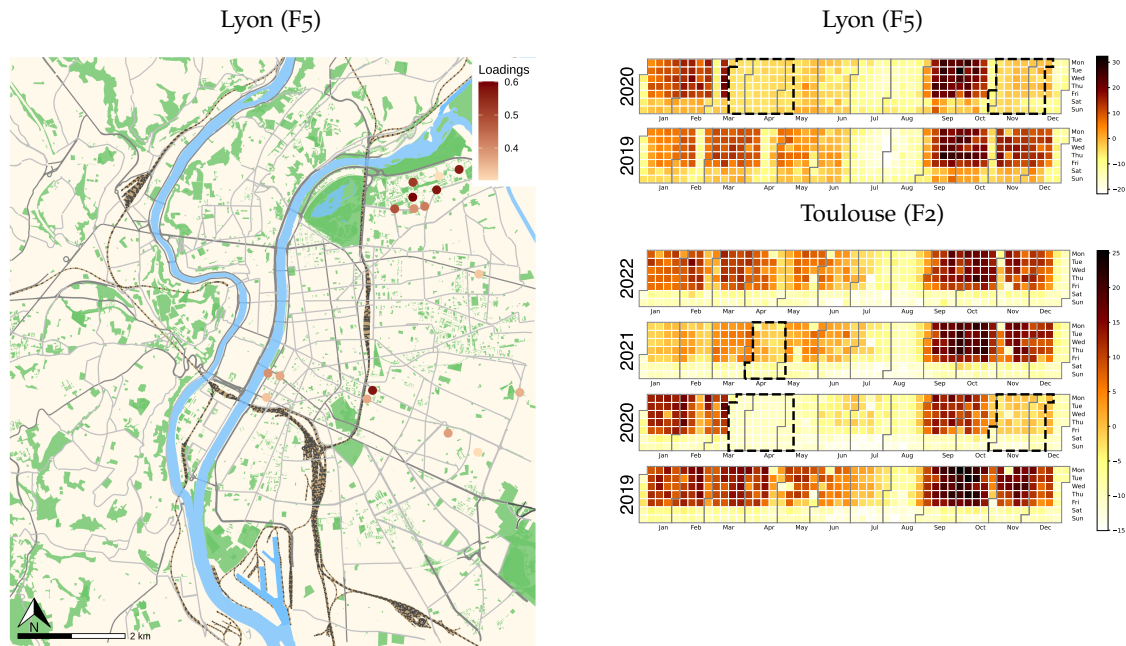


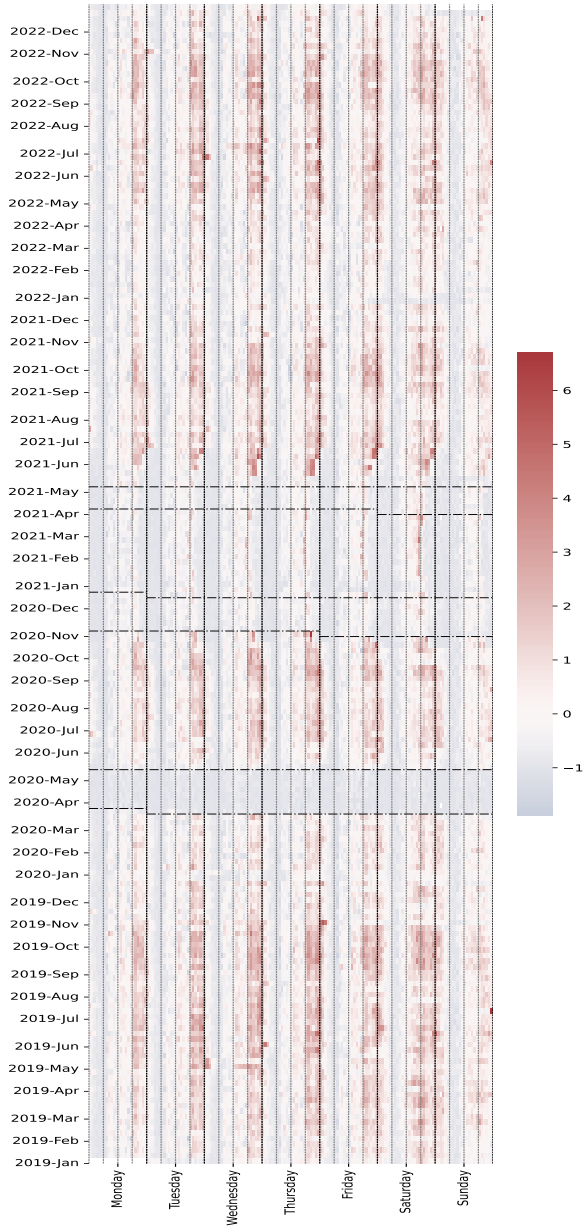
Figure 9: Factors representing university student BSS usage in Lyon (5th factor) and Toulouse (2nd factor). The Lyon loading map shows that the main active stations are near the 3 universities. The right figures are daily representations of the corresponding factors, that is each unit square is a day in the year whose color gives the intensity of the corresponding factor. Lockdown periods are delimited by dotted lines.

5.2 The late-evening and night-time factor

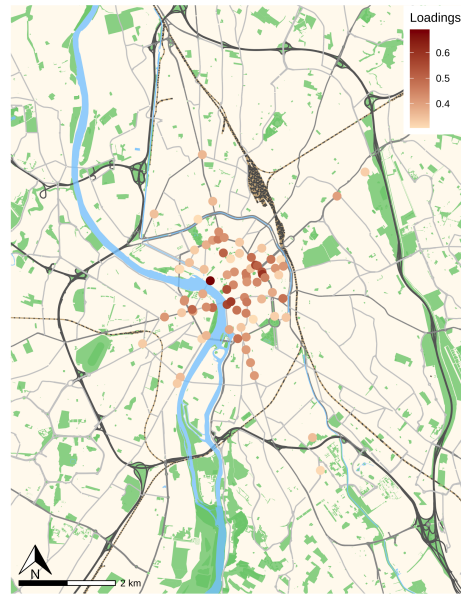
The third factor in Toulouse and second one in Lyon, each respectively accounting for 7.4% and 7.9% of the variance, are highly representative of the late-evening and night-time activity (Figure 10). Within the week, the intensity of these factors is less pronounced on Mondays and Sundays and predominant on Saturdays when bike sharing starts earlier. Within the year, it is mainly distributed from May to November. This distribution over the year, that keeps winter and months around winter out, was not observed for the factors largely concerned by students (factor 2 for Toulouse and 5 for Lyon).

Loading maps pinpoint bike stations close to areas with high concentration of bars, restaurants and other leisure activities (e.g., Hotel de Ville, Bellecour, Berges du Rhone, and La Guillotiere in Lyon, Place Saint Georges, Place du Capitole, Place Esquirol and Place Saint-Pierre in Toulouse). Our results for Lyon, for example, are consistent with those of [20] where urban nighttime centralities are studied. Interestingly, the two curfews imposed at 9PM starting from mid-October 2020 and at 7PM starting from 20 March 2021 are clearly visible (see supplementary materials for a zoom plot of the first curfew). For both we observe a peak of traffic during the hour right before the curfew, probably due to people using bikes to go back home.

Toulouse (F3)



Toulouse (F3)



Lyon (F2)

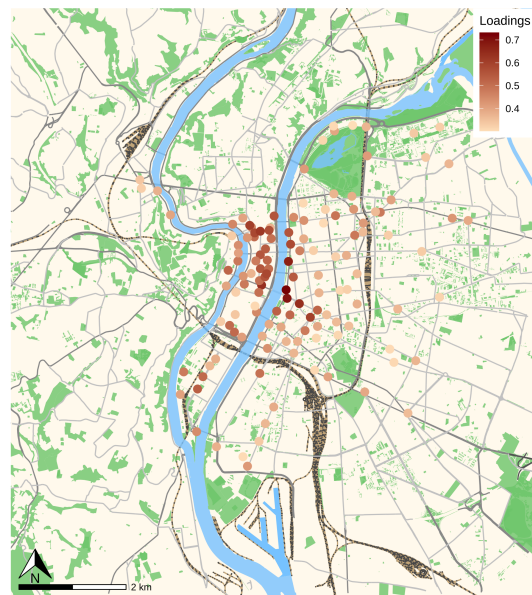


Figure 10: (left) Hourly representation of the late-evening and night-time factor in Toulouse. There are no main differences between the two towns, so only Toulouse is represented here. (right) Loading map of the departure BSS traffic associated to these factors for both Toulouse and Lyon.

Finally, the inter-lockdowns period in 2020 has a profile very similar to the rest of the year in both towns, which shows the resilience of the population concerned.

5.3 The need to be outdoors: markets, parks and stadiums

EFA models for both Lyon and Toulouse restricted to years 2019 and 2020 provide one factor (the 6th for Lyon and the 5th for Toulouse) representative of BSS usage near parks and stadiums (Figure 11): Ile Barbe, Saint-Rambert, Tête d'Or, Mulatière and Gerlan in Lyon, Sept Deniers, Jardins Raymond VI, Prairie des Filtres, Jardin des Plantes and les Argoulets in Toulouse. Scores are high during weekends, and higher in 2020 comparing to 2019. It can be noted that on the first weekend after the end of the first lockdown (16 and 17 May 2020), bike traffic gets back to pre-pandemic levels near parks and, in an unusual way, remains high during the following two weeks (particularly in Lyon), even though this period did not correspond to vacation time and schools had reopened.

This factor disappears for Toulouse if we consider an EFA model for years from 2019 to 2022 and is probably distributed over other factors. However, the sixth factor in the T2 EFA model for Toulouse (2019-2022) explicitly represents open-air markets (Figure 12). Its high values are concentrated in the three stations Saint Aubin Camichel, Victor Hugo and Colombette, on Sunday around midday when the Sunday marketplaces have a peak of activity. Such factor can be again interpreted as a need to get out into open and green spaces. These marketplaces were closed during the first lockdown but remained open during the second and the third lockdowns. It is remarkable to see how the level of activity at these stations has remained almost constant throughout the pandemic, except during the 1st lockdown.

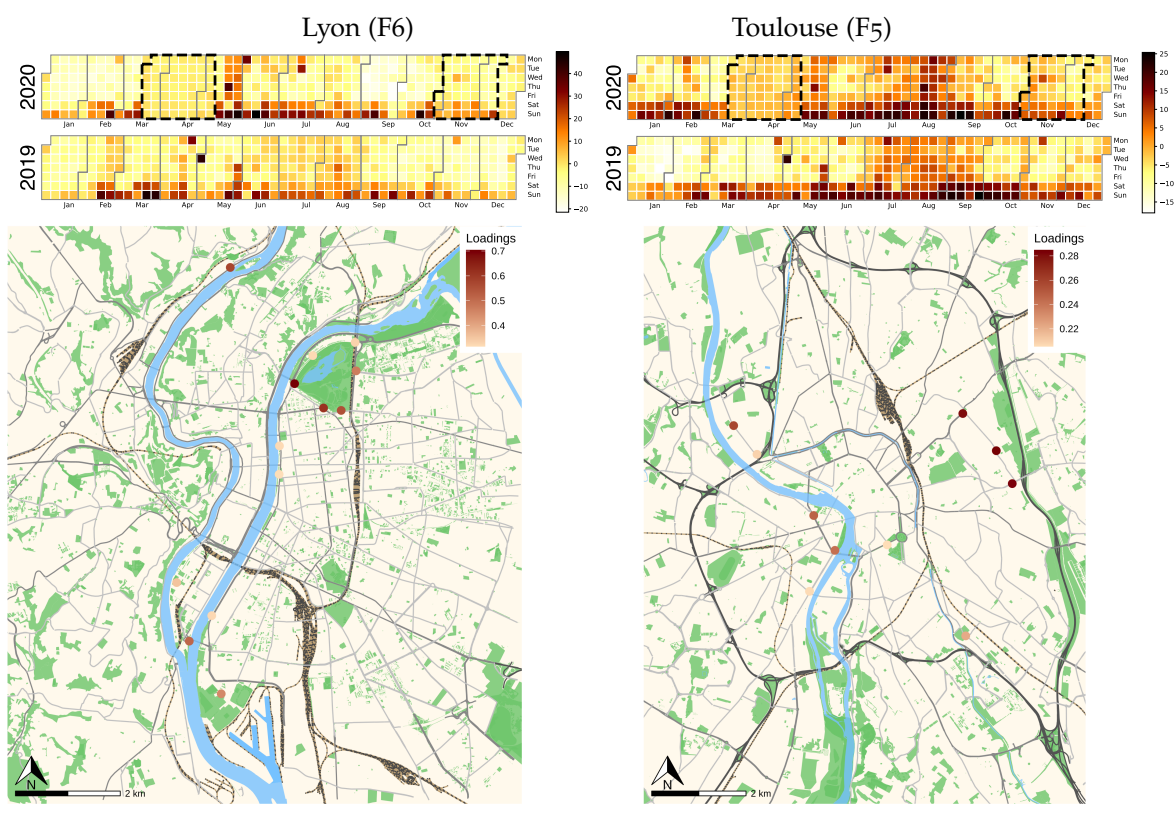


Figure 11: The EFA factors relative to parks and stadiums BSS in Lyon (left) and Toulouse (right) for models based on years 2020 and 2021. (top) Daily representations of the corresponding factors. (bottom) The loading maps with stations whose intensity loadings are greater than .3 for Lyon and greater than .2 for Toulouse.

Toulouse (F6)

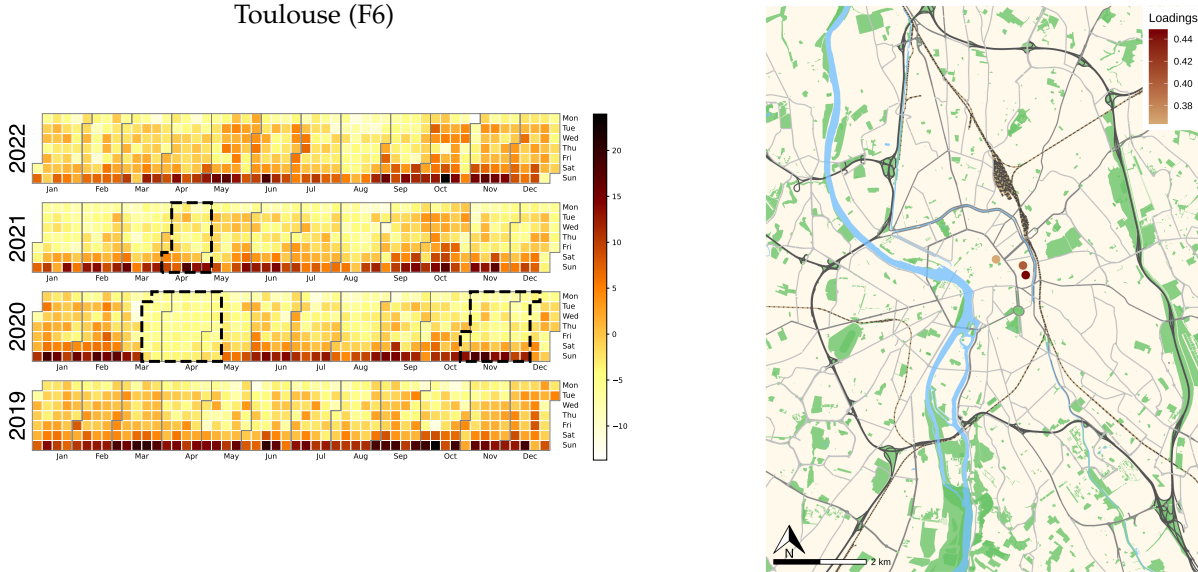


Figure 12: The 6th EFA factor in Toulouse relative to the open-air-markets.

6 Conclusion

In this paper, we investigate the evolution of Bike-Sharing System (BSS) usage for two French cities, Toulouse and Lyon, during the COVID-19 pandemic situation.

In the first part, we analyze the evolution of bike rental numbers across both towns from 2019 to 2022, utilizing a 10-minute time granularity. For this analysis, data from all dock-stations have been aggregated, thus excluding any spatial considerations. The results demonstrate that these time series can be effectively explained by the interplay of two main components: the annual tendency and daily evolution, each influenced by the pandemic's progression. While the components for 2019 and 2022 share considerable similarities, the same cannot be said for the peak pandemic years of 2020 and 2021. Notably, 2021 serves as a transitional year, with its daily and annual components bearing closer resemblance to 2019 and 2022 than to 2020, despite the ongoing pandemic. This phenomenon could be attributed to an adaptation to living with the pandemic and possibly a renewed sense of security fostered by the vaccination campaign.

Among the most relevant changes in the daily evolution of BSS usage between 2019 (without COVID) and 2020 (with COVID), the global network level analysis shows a proportional increase of BSS use during late morning and early afternoon for working days, in both towns. Nevertheless, the four daily peaks of traffic remain located at the same time for all the years in both towns (with the only exception of weekend midday peaks that are 15-minute later in Toulouse than in Lyon, in 2019 and 2020), which indicates that people who continued to use BSS probably did not change their habit. Concerning BSS traffic volumes, morning peaks appear as the most impacted by the pandemic, particularly in Toulouse, but less impacted than reported in many similar previous studies. Yearly component of the models show that the BSS traffic profile in Lyon is definitely more than resilient, it displays a boost of activity between the two 2020 lockdowns (from mid-

May to end of October), which Toulouse does not. For both cities, the effects of the second and third lockdowns are much more weaker than those of the first lockdown. Road traffic and Public-Transport have been much more impacted than BSS. By 2020, none of them appears to get back to pre-COVID levels. After the first lockdown, with a similar 1-month delay and until the second lockdown, with the exception of summer holidays, 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 towns, 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 towns.

Consistent with previous studies, we found that BSS trip duration significantly increased during the pandemic period for working-days and weekend-days.

In a second part, we use Exploratory Factor Analysis (EFA) to derive spatio-temporal patterns in BSS usage. 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 that of the entire network as in the first part of the study. Both towns display a morning peak mostly associated with departures from residential areas. This is particularly noticeable in the city of Toulouse, where residential areas appear to be more separate from business ones. An end-of-afternoon peak of BSS traffic is clearly detected by EFA with respect to areas with high density of business and activity centers in the city of Lyon, while it covers a large portion of the whole city center of Toulouse. This BSS usage profile appears to take longer to get back to pre-pandemic levels in Toulouse than in Lyon, even though this phenomenon may be partially explained for Toulouse by student activity (and the related summer holiday break) associated to dock stations included in this pattern. For Lyon, a specific factor is associated to student activity, clearly showing the prolonged effect of lockdown, restrictions and holiday breaks which affected student-related bike usages. Such a specific students spatio-temporal pattern does not exist in the Toulouse models.

Interestingly, the EFA analysis clearly identifies a BSS usage pattern in the proximity of parks and stadiums for both cities. After the first lockdown, BSS traffic near these zones appears to be relatively higher in 2020 than in 2019, during weekends and, surprisingly, during the two weeks following the end of the lockdown despite the fact that it was not a vacation period. This could indicate the population's need to reconnect with social and nature activities after lockdown stay-at-home restrictions.

Our results globally show that BSS appeared as a resilient mobility alternative during the pandemic situation. It probably indicates an increased preference towards cycling in general. Without surveys, it is however difficult to know which part of the road-traffic decrease can be put down to some new cycling usage, to smart working, or other mobility choices. For this reason, as future research is to shed light on this question, we aim to complete this study by coupling it with an analysis of surveys that are being currently collected in the two analyzed cities. The findings of this paper could help transport operators and public authorities better identify and understand cycling behavioral changes in order to respond even more efficiently to an emergency situation, such as the one created by the pandemic. They also provide some keys to better understanding the current opportunities in terms of bicycle use and to set up the conditions for the perpetuation of new cycling practices towards a more resilient and efficient mobility.

7 Author contribution and Acknowledgments

All authors whose names appear on the submission made substantial contributions to the acquisition, analysis, or interpretation of data, drafted the work, and approved the submitted version.

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On behalf of all authors, the corresponding author states that there is no conflict of interest.

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