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“Covid-19 impact on bike-sharing systems: Lessons from Toulouse and Lyon”

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COVID-19 impact on bike-sharing systems: Lessons from Toulouse and Lyon[1]

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Abstract

Based on bike-sharing systems (BSS) data in Toulouse and Lyon, this study examines the impact of COVID-19 on relevant variables to BSS usage. Our findings indicate significant changes in longer travel distances, which would be explained by users who use the BSS at peak hours. Also, there is evidence of a higher willingness to use BSS under adverse weather conditions (such as rain and wind), less substitution with the public transport system in Lyon, and recovery and even a slight increase of BSS trips for Toulouse and Lyon, respectively. These results suggest long-term changes in user habits, offering an excellent opportunity to develop public policies to promote cycling further.

Keywords: bike-sharing system, COVID-19 effects, long-term changes.

JEL Classification: R40, L91.

1 Introduction

The COVID-19 outbreak posed significant challenges worldwide, requiring extensive public health efforts. Governments implemented various measures to contain the virus, such as stay-at-home orders to restrict people's mobility. (See Xiong et al., 2020b.) While primarily

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focused on public health, the measures impacted several economic sectors, such as transportation, by restricting traffic, international flights, and other forms of transportation.

As public transport was considered a source for spreading the virus, it was particularly affected by social distancing measures. In this context, bicycles emerged as a flexible, efficient alternative that was both compatible with the health crisis and environmentally friendly.[4] (See Hu *et al.*, 2021; Nikiforiadis *et al.*, 2020). This paper aims to analyze the changes in BSS usage since the COVID-19 outbreak and suggests potential public policies to encourage cycling.

BSS are not new in our society; they have exponentially spread in the last decade since they provide a low-carbon solution to the “last mile” problem. (See Shaheen *et al.*, 2010.). The first publicly accessible bike-sharing goes back to 1968 when the “White Bicycles” was deployed in Amsterdam. It was a complete failure due to its lack of security measures. After that, different generations of BSS were developed. Shaheen *et al.* (2010) detailed the characteristics of three different BSS generations and proposed a fourth one: electric bikes with solar-powered docking stations, locking mechanisms that avoid theft, and redistribution systems linked to public transit smartcards.

Bike-sharing development has positively influenced cycling in many cities. (See Shaheen *et al.*, 2012; Eren & Uz, 2020.) For example, in Lyon, 150,000 car trips were replaced by 2 million bicycle trips in the first six months after the introduction of its BSS, Velo'v. (See Bührmann, 2007.) One year after Velo’v’s introduction, bicycle trips had increased by 44% compared to the year before. In Paris, Vélib' (the capital’s BSS) consisted of 16,000 bikes and 1,200 stations one year after launch, translating to an average of 75,000 trips a day. (See Luc, 2008.) Two-thirds of Vélib' users say these trips are usually part of a more extended trip, and 1 in 5 users drove less than before the BSS was launched. (See Luc, 2008).

Although the literature on bike-sharing usage is not recent (See for instance Ricci, 2015; or Fishman, 2020), studies on its post-COVID-19 evolution remain scarce. Indeed, research has focused on the decline in human movement caused by COVID-19 but not many studies have solely focused on cycling changes. (See Hu et al. 2021.)

For example, after the COVID-19 outbreak in Zurich, statistical analysis revealed that passengers used the BSS for longer and farther trips than before. While e-scooter usage saw minor changes, bike and e-bike services showed significant variations. Home, Park, and Grocery trip activities increased, whereas Leisure and Shopping activities declined. During the pandemic, there was a noticeable shift towards micro-mobility commuting to workplaces. (See Li et al.,2020.)

Another recent study for Beijing by Chai *et al.* (2020) shows that BSS trips fell by 64.8% during the outbreak, followed by an increase of 15.9%, suggesting that productive and residential activities have only partially recovered. On the other hand, a study for New York by Teixeira and Lopes (2020) shows that the BSS has been more resilient than the subway

[4] European Cyclists´ Federation (2019) calculates that riding a bike accounts for 21g of C02 emissions per km (production emissions) compared to 271g per passenger-kilometer that a car produces.

system, with a less significant drop in the number of users (BSS use fell by 71% versus a 90% dropped for the subway system) and an increase in the average trip duration (from 13 to 19 minutes per trip).

Our paper partially mirrors Hu, Xiong, Liu, and Zhang's (2021) study on spatiotemporal changing patterns of BSS usage during COVID-19 with some data availability and methodology differences. For example, while we both found a relevant decrease in bike usage due to the COVID-19 confinement, they could disaggregate the effect into a decrease in membership trips and an increase in casual trips. We have also found a fall-rebound pattern that seems to identify BSS as a resilient option under the demand shock caused by the COVID-19 pandemic.

Some studies show that the pandemic may lead to long-term changes in public transport usage, with increased bicycling and walking. (See De Vos, 2020; Batty, 2020; and Megahed & Ghoneim, 2020.) However, a regression model studying the responses to a survey in Thessaloniki (Greece) revealed the unwillingness of respondents to change their BSS usage. (See Nikiforiadis et al., 2020.)

Given the current circumstances, it is worth examining how bicycle habits evolved after the COVID-19 outbreak and whether any changes in habits are permanent. These questions are relevant given the challenges associated with changing transportation habits. Therefore, COVID-19 offers us an excellent opportunity to study this sector.[5]

Considering this framework, this research aims to measure, using econometric tools, the effect of key variables on BSS usage and to see if these effects change after the COVID-19 outbreak. Our analysis focuses on two cities in France, Toulouse and Lyon, focusing on their similarities and differences.

This paper is organized as follows. Section 2 presents the data and a descriptive analysis of the available information. Section 3 develops the econometric model and the methodology. Section 4 shows the econometric results for the cities of Toulouse and Lyon. Finally, Section 5 presents the conclusions and policy implications.

2 Data and descriptive analysis

2.1 Primary dataset and sources

The primary dataset comprises origin-destination ("O&D") bike trips provided by JC Decaux for 2019 and 2020 for two French cities, Lyon and Toulouse. Each observation includes the origin and destination stations and start-end trip times (format date-hour-minute). For each bike station, we have the coordinates (latitude and longitude) and the IRIS area ("IRIS area"

[5] Replies to these questions have also been proposed by Rocci (2015) and Moro *et al.* (2018).

or just "area") where each bike station is located.[6-7] Toulouse's dataset contains 6,943,375 observations, while Lyon's has 15,586,007.

Additionally, we incorporate weather data from MeteoFrance,[8] focusing on four variables: (i) Rain (in milliliters), (ii) Wind speed (in meters per second), (iii) Temperature (in degrees Celsius), and (iv) Solar radiation (in Joules/CM^2). This data is aggregated at day-hour levels for 2019 and 2020 and matched to each trip's start and end times in the primary dataset.

We also include data on public transport usage for Toulouse and Lyon, covering Bus, Metro, and Tram usage for the same years. Tisséo Collectivité provided the data for Toulouse, which is daily, and Sytral provided the data for Lyo, which is hourly. This data is likewise matched to the start and end times of each bike trip.

Demographic data from the French Census of 2017 is used.[9] This data is aggregated by IRIS area for each city. It includes information on population size by area, gender distribution, economic sectors, education levels, and more. This demographic data matches the bike stations' start and end locations (IRIS area) in our primary dataset.

Furthermore, we use information from the Permanent Equipment Base (BPE) in France,[10] which provides data about services and amenities in each IRIS area during 2019. For instance, this includes the number of restaurants, universities, police stations, health centers, pharmacies, gyms, museums, etc., in each city area. Likewise, based on the IRIS area code, these are also matched to the start and end locations of each bike trip.

Using the bike station's coordinates (latitude and longitude), we calculate the distance between them using an open-source provider (HERE), which provides the distance (in kilometers) a car would travel between stations. Each trip's travel time (in hours) is calculated from the start and end times in the primary dataset.[11]

To account for other transportation modes not observed in our model, such as cars or walking, we create an outside option variable based on public transport data for Toulouse and Lyon.[12]

[6] The IRIS is a 9-digit numeric code representing a homogeneous infra-municipal territory division with identifiable and stable contours over time and a target size of 2,000 inhabitants per zone. Municipalities with at least 10,000 inhabitants and a high proportion of municipalities with 5,000 to 10,000 inhabitants are divided into IRIS areas. For more information, visit: < https://www.insee.fr/fr/metadonnees/definition/c1523>.

[7] To obtain the IRIS area of each BSS station, we used the Géoportail web portal. For more details, visit <https://www.geoportail.gouv.fr/carte>.

[8] For more information, visit: <https://meteofrance.com/>.

[9] For more information, visit: <https://www.insee.fr/>.

[10] The permanent equipment database (BPE) is a statistical source that provides the level of equipment and services provided to the population in a territory. The results are offered in the form of databases in different formats and for two geographical levels: communes and IRIS areas. For more information, visit: <https://www.insee.fr/>.

[11] HERE is a global company serving thousands of customers at scale. Collecting data from over 100,000 sources and with 80 billion API calls per month HERE can offer a fresh and accurate digital representation of the world, from precisely tracking the location of assets to providing carriers with live road updates to find the fastest routes. For more information, visit: <https://www.here.com/>.

[12] The methodology is explained in Appendix A.

Finally, in our primary dataset, we identify the day of the week (Monday, Tuesday, etc.) and type of day in France (Public holidays, School vacations, Ordinary and Summer) in 2019 and 2020.[13-14-15]

Tables 1 and 2 present statistical summaries of selected variables for Toulouse and Lyon.

Table 1: Statistical summaries. Selected variables for Toulouse

	(1)	(2)	(3)	(4)
VARIABLES	Mean	Standard deviation	Minimum	Maximum
Travel distance (km.)	2.355	1.526	0	21.557
Travel time (hrs.)	0.267	3.952	-0.95	1742.717
Rain	0.0459	0.374	0	20.5
Temperature	16.978	7.622	-5	39.8
Wind speed	4.236	2.436	0	18.7
Sola radiation	80	94.679	0	352
Bus users	163325	80,076	0	303,913
Metro users	298060	121,266	0	509,586
Tram users	33838	14,560	0	59,823

Table 2: Statistical summaries. Selected variables for Lyon

	(1)	(2)	(3)	(4)
VARIABLES	Mean	Standard deviation	Minimum	Maximum
Travel distance (km.)	2.557	1.603	0	27.530
Travel time (hrs.)	0.243	2.479	-1	4669.883
Rain	0.0530	0.444	0	26.5
Temperature	16.083	8.353	-5	39.7
Wind speed	3.599	2.557	0	17.6
Sola radiation	74	92.166	0	349
Bus users	21669	15,009	1	61,261
Metro users	23172	15,150	1	65,061
Tram users	11466	7,349	1	32,426

[13] In 2019, the public holidays in France were: 1/1/2019; 22/4/2019; 1/5/2019; 8/5/2019; 30/5/2019; 10/6/2019; 14/7/2019; 15/8/2019; 1/11/2019; 11/11/2019; and 25/12/2019. Likewise, the public holidays in 2020 in France were: 1/1/2020; 13/4/2020; 8/5/2020; 21/5/2020; 1/6/2020; 14/7/2020; 15/8/2020; 1/11/2020; 11/11/2020 and 25/12/2020.

[14] The school vacation period considers the fall, Christmas, winter, and spring vacations in France. Autumn vacations: 19/10/2019 to 03/11/2019; and 17/10/2020 to 31/10/2020. Christmas vacations: 02/01/2019 to 06/01/2019; 21/12/2019 to 31/12/2019; 02/01/2020 to 05/01/2020; and 19/12/2020 to 31/12/2020. Winter vacations: 02/23/2019 to 03/10/2019; and 02/08/2020 to 02/23/2020. Fall vacations: 04/20/2019 to 05/05/2019; and 04/04/2020 to 04/19/2020.

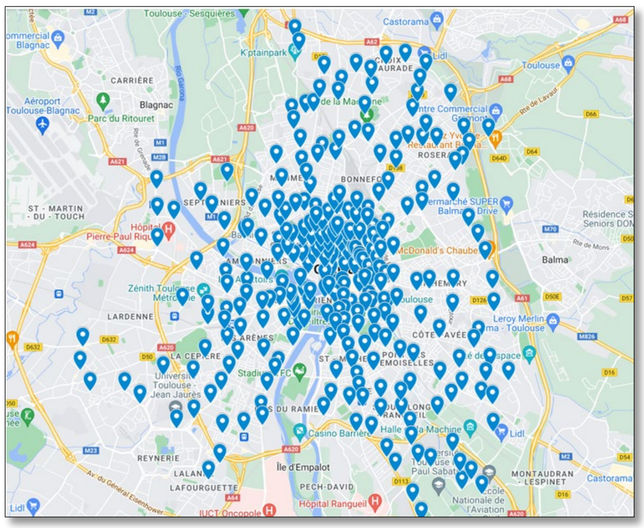
[15] The summer period considers: 06/07/2019 to 01/09/2019; and 04/07/2020 to 31/08/2020.

2.2 Descriptive analysis

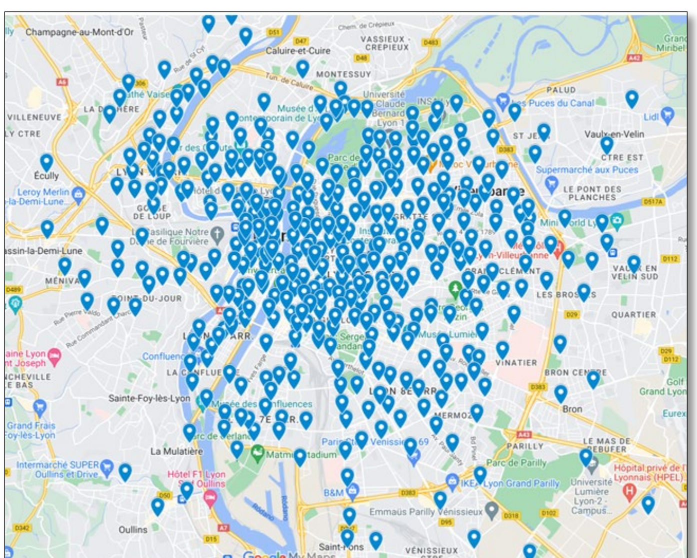
The BSS in Toulouse and Lyon work on docks, meaning there are predefined bike stations where bikes can be picked up and dropped off. The fare scheme is mainly based on temporary subscriptions, allowing unlimited bike trips with the first 30 minutes of each trip free.

We have 283 docks in Toulouse, with only standard bikes (i.e., no electric versions). Graph 1 shows their geographical distribution. In Lyon, the BSS offers standard and electric bikes, with 428 docks, as depicted in Graph 2.

Graph 1: BSS docks in Toulouse

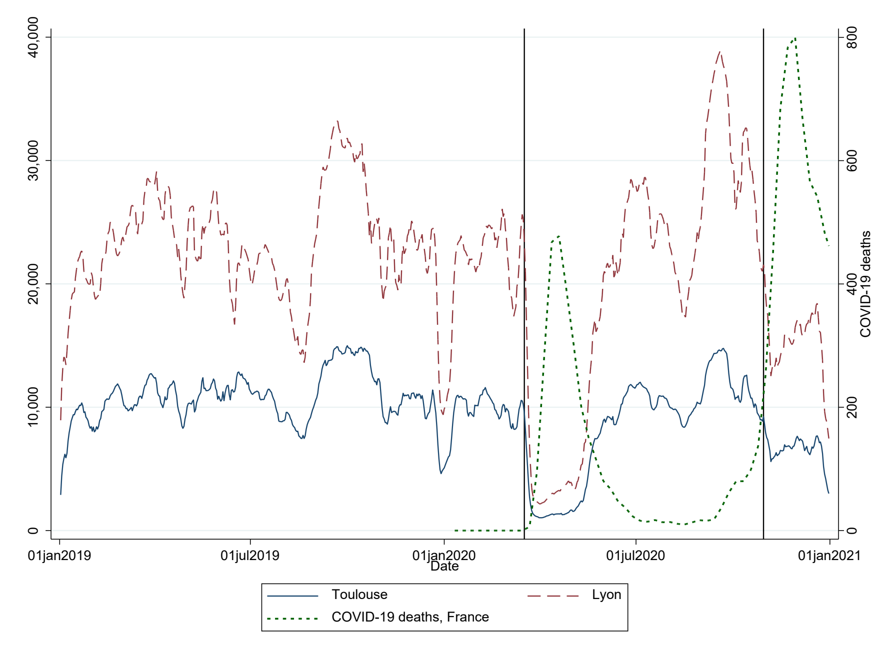


Graph 2: BSS docks in Lyon



To exhibit the impact of COVID-19, we examine variables directly affected by the first lockdown and social distancing measures, such as travel time and distance, trip start time, and bike use between weekdays. Graph 3 shows the daily trips for both cities, smoothed by a 7-day moving average.

Graph 3: Daily trips in Toulouse and Lyon

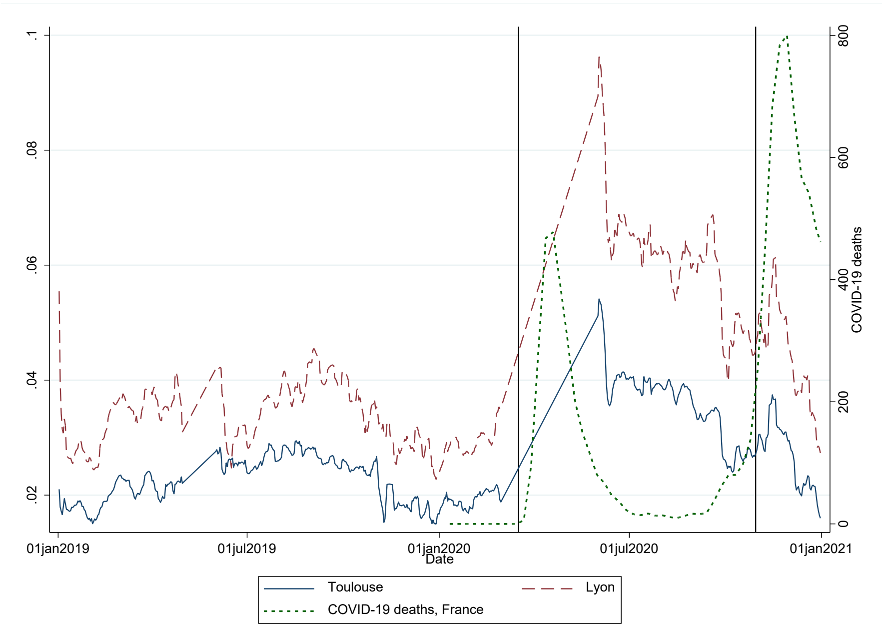


Note: Black vertical lines refer to the start of the first and second lockdown periods in France. Data is filtered by a 7-day moving average. COVID-19 deaths in France were obtained from Our World in Data.

For Toulouse (blue/navy line on Graph 3) and Lyon (red/brown dash line), we observe a sharp decrease in the number of daily BSS trips after the COVID-19 outbreak in March (the start of the first lockdown). Then, a significant recovery is shown, almost to levels before the first confinement, although with increased variability and a drop since November 2020 (the start of the second lockdown).

Graph 4 presents the daily share of BSS trips over public transport usage (Bus, Metro, and Tram) by a 7-day moving average. We can highlight two points. First, bike use is less prevalent than the public transport system, accounting for 1% and 4% of their combined traffic. Second, the BSS was more resilient than the public transport system. Indeed, after the first lockdown in France, there was a significant jump in the bike share for both cities, which remained relatively high until almost the beginning of the second confinement in France. These results provide the first insights into a higher willingness to use bikes after the first confinement. Appendix B provides data on public transport usage for Toulouse and Lyon.

Graph 4: Daily BSS share over the public transport system for Toulouse and Lyon

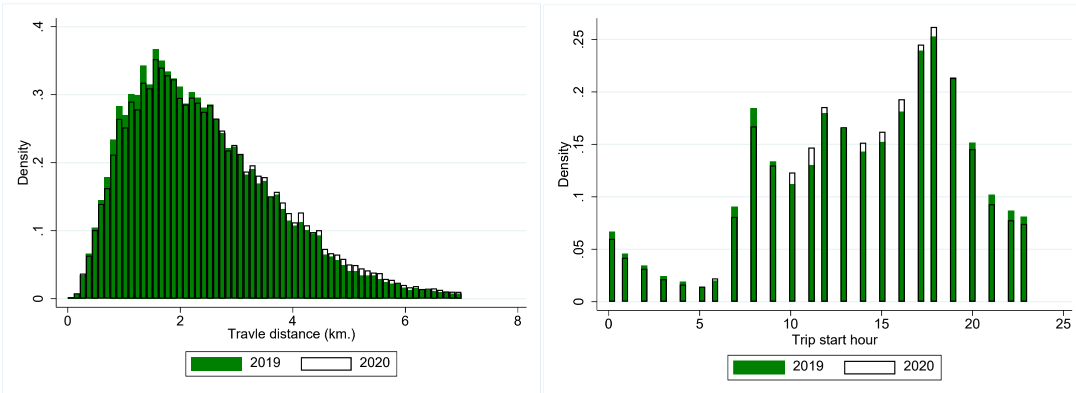


Note: Black vertical lines refer to the start of the first and second lockdown periods in France. Data is filtered by a 7-day moving average. COVID-19 deaths in France were obtained from Our World in Data.

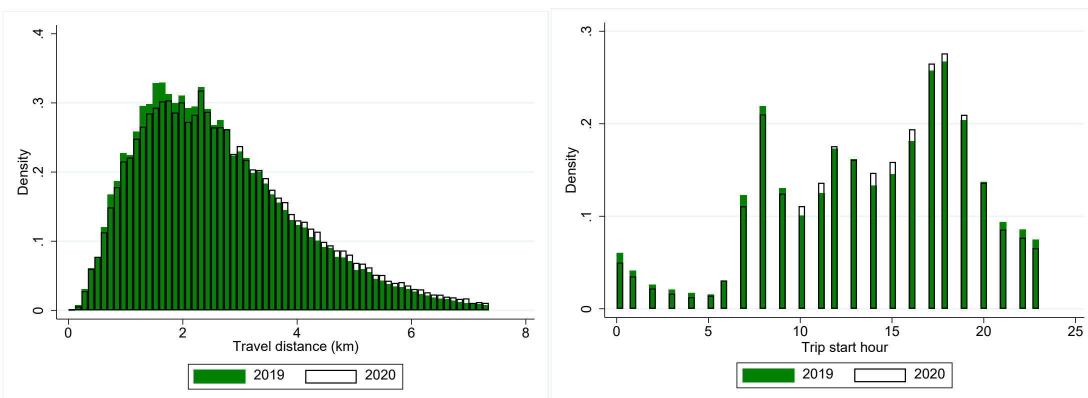
Graphs 5 and 6 present density histograms of travel distance (in kilometers) and starting hours of bike trips for both cities. Histograms in 2019 are presented in green bars; histograms in 2020 are represented by transparent bars with a black outline. First, the graphs show a rightward movement in the travel distance density histogram for both cities, as cyclists were more likely to take longer distance trips in 2020 compared to 2019. For trip starting hours, bike trips were more concentrated between 10:00 and 18:00 hours for both cities in 2020 compared to 2019, explained by COVID-19 measures in France, such as curfews.

Graphs 7 and 8 below show the density histograms for the travel time and day of the week variables. Again, for 2019, we have green bars; for 2020, we have transparent bars with a black outline. The travel time graphs show a rightward movement for both cities; longer travel times are more likely in 2020 compared to 2019. This aligns with the higher travel distances previously seen. On the other hand, there was no significant variation in the daily distribution of BSS trips between 2020 and 2019 for both cities.

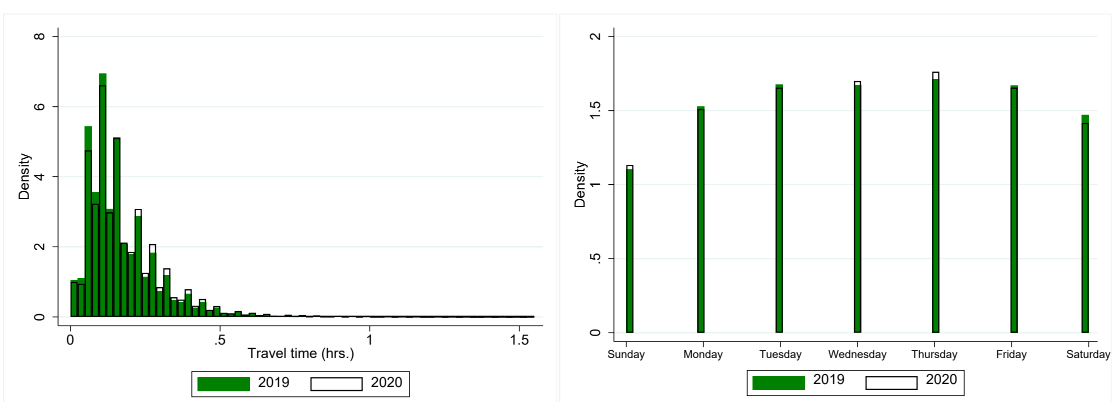
Graph 5: Density histogram of travel distance and trip start hour for Toulouse



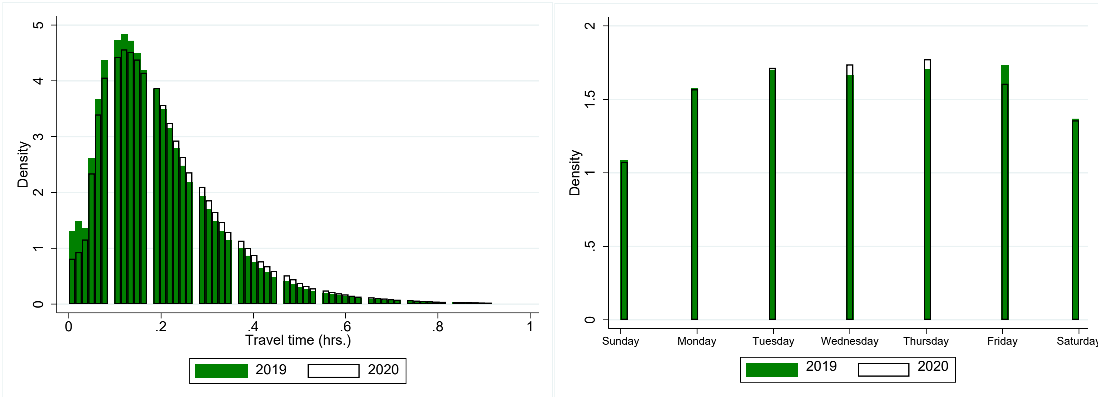
Graph 6: Density histogram of travel distance and trip start hour for Lyon



Graph 7: Density histogram of travel time and day of the week for Toulouse



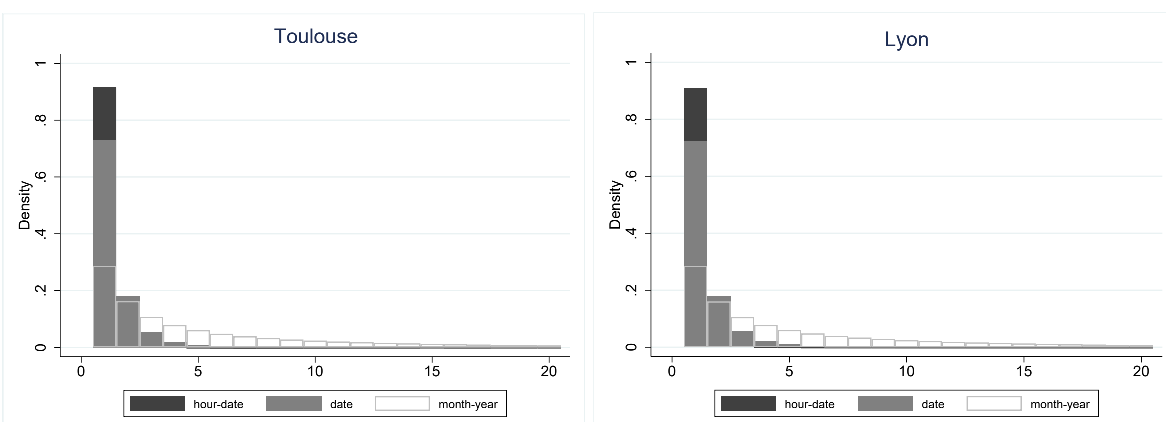
Graph 8: Density histogram of travel time and day of the week for Lyon



Finally, Graph 9 shows the distribution of the number of bike trips over different time windows (hourly, daily, and monthly). First, the longer the time window, the more bike trips per time window. This is important because it shows a trade-off for an econometric analysis considering the number of trips as a dependent variable.

In fact, if we consider the number of bike trips at the hour-day level (low aggregation): [i] our dependent variable will have a smaller variance, which is undesirable since it is necessary for econometric analysis; however, [ii] it also maximizes the variability of the explanatory variables, which is desirable to identify the effect of each regressor better. In the opposite case (i.e., number of bike trips per month), the trade-off goes in the opposite direction (larger dependent variable variance but lower regressors' variability). Data aggregation is an important issue, which will be discussed in more detail in the next section.

Graph 9: Density histogram of the number of bike trips per time window



3 Econometric methodology

3.1 Specification

Given that the number of bike trips using BSS is a counting variable, it can be modeled using a Poisson distribution,[16-17] where the average number of bike trips ($\lambda_{o,d,t}$) by origin (o) and destination (d) every period (t), is expressed as the exponential of a linear combination of independent regressors, grouped into three sets: [i] O&D[18]-specific variables (X_{od}); [ii] origin-specific (X_o) and destination-specific (X_d) variables; and [iii] non-O&D-specific variables (X_t).

$$\lambda_{o,d,t} = exp\ (\alpha_{od}X_{od} + \alpha_o X_o + \ \alpha_d X_d + \ \alpha_t X_t) \qquad (1)$$

To capture the COVID-19 impact on these variables, the parameters are specified as follows:

$$\alpha_i = \alpha_{oi} + \alpha_{1i}D\ ;\ \ i\ \epsilon\ \{od, o, d, t\} \qquad (2)$$

where:

$$D = \begin{cases} 0, & for\ the\ period\ before\ 1^{st}\ confinement\ in\ \ France \\ 1, & otherwise \end{cases}$$

Here, α_{oi} represents the partial effect for each regressor before the first confinement in France, while $\alpha_{oi} + \alpha_{1i}$ represent the effect after the first lockdown.

The focus is on α_{1i}, which measures the change between the pre- and post-lockdown periods, serving as our proxy for the COVID-19 effect on these variables.

The first lockdown in France lasted from March 17 to May 10, 2020.[19] For simplicity, we assume it lasted from March to May 2020. [20] Thus, the pre-first confinement period consists of 2019 and January-February 2020, while the post-first confinement period covers June-December 2020.

3.2 Variables' selection

Based on our model, we now specify the dependent variables and regressors for each vector: [i] O&D-specific variables (X_{od}); [ii] origin-specific (X_o) and destination-specific (X_d) variables; and [iii] non-O&D-specific variables (X_t).

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[16] Models like Poisson regression is recognized by researchers as better option for this specific context. (See Faghih-Imani *et al.*, 2014; Noland *et al.*, 2016; Wang *et al.*, 2016). For more details, see Greene (2017).
[17] Based on the deviance and Pearson goodness-of-fit tests respectively, we cannot reject the hypothesis that our data fit the Poisson distribution. Moreover, after performing a negative binomial regression, the results converge to the Poisson regression.
[18] O&D means an origin and destination trip between 2 specific bike stations, directionally.
[19] May 11, 2020, is known as the "first stage opening." (See Ivaldi and Palikot, 2020.)
[20] We consider this assumption because (i) mobility was already affected by the vast amount of cases spreading in Europe right before the first lockdown was implemented, and (ii) the complete deconfinement was carried out in several stages, ending by the end of May 2020.

The dependent variable of our model is the number of bike trips per hour-day. As explained in the previous section, this maximizes the variability and explanatory power of our model as most regressors are hour-day, such as weather variables (Rain, Temperature, Wind speed, and Solar radiation) and public transport variables (Bus, Metro, and Tram users for the case of Lyon).

For the O&D-specific variables (X_{od}) we consider Travel distance (in km.) and Travel time (in hours).

- We expect a negative effect on the Travel distance variable since longer trips should discourage bike usage. The Travel time variable, meanwhile, should have a positive effect since, on average, people should not use bicycles for very short trips (due to the lack of docks nearby or because walking is more time-efficient).

Related to the non-O&D-specific variables (X_t), we use weather variables (Rain, Temperature, Wind speed, and Solar radiation), public transport variables (Bus, Metro, and Tram users, respectively), day of the week (Monday, Tuesday, etc.), type of day (Public holiday, School vacations, Ordinary and Summer), and fixed effect by month.

- On average, we expect a negative effect of the variables Rain, Wind speed, and Solar radiation on bike usage due to unfavorable weather conditions or situations that may affect health/safety. Similarly, we expect a positive effect of Temperature on bike usage since people should not use them at low temperatures. Likewise, we expect a negative effect of public transportation regressors due to the substitution with the BSS.

Finally, considering the origin-specific (X_o) and destination-specific (X_d) regressors, we use information from the French Census and the BPE to characterize the starting and ending area of each bike trip.

- Regarding the demographic data (French Census, 2017), we pay attention to variables related to the probability of getting COVID-19 and those that, in case of having caught the virus, could increase its severity (risk factors). Then, we focus on the following regressors: the Number of people, Average age of people, Student proportion, Foreigners proportion, Women proportion, Mode of the highest education level, Mode of the number of people per household, Mode of the household family structure; Mode of transportation mode for commuting; Mode of the number of vehicles per household; Mode of the type of activity performed by the person; and Mode of the person's socio-professional category.
- Finally, for amenities/services data (BPE, 2019), we pay attention to those variables that are related to people's daily activities, as well as those related to leisure. We chose the following variables: Number of banks, Number of restaurants and bars, Number of supermarkets, Number of colleges and universities, Number of health

centers, Number of pharmacies, Number of taxis and VTC[21] ("chauffeur-driven vehicles"), Number of outdoor playgrounds and play areas, and Number of cinemas.

3.3 Estimation procedure

Our model is nonlinear (Poisson model); we use Maximum Likelihood Estimation to estimate the parameters simultaneously. All regressions use the robust standard error due to potential heteroscedasticity (White, 1980). Given the use of actual data, our estimates are more reliable. Although we do not have information on bike availability per dock, capacity constraints are mitigated by the variation in bike trip timing during the day. Finally, we estimate our model for each city, Toulouse and Lyon, separately to help us better compare their results.

We perform robustness checks as follows. First, we estimate our Poisson model for four different periods/cohorts:

- The first regression estimates our model as explained in Section 3.1: the pre-first confinement period from January 2019 to February 2020 compared to the post-first lockdown period from June to December 2020.
- The second regression only compares 2020 and 2019 from June to December, aiming to avoid seasonal effects.
- The third regression compares 2020 and 2019 from June to October. This seeks to isolate the period without relevant COVID-19 measures and low COVID-19 cases in France.
- The fourth regression exclusively compares 2020 and 2019 in November and December, aiming to show the estimates during the second lockdown in France, which started on October 30, 2020.[22]

These robustness checks dynamically test the consistency of our estimates. The results from the third regression are the most suitable for future projections, as they represent the "pseudo-normal" after the first confinement in France. Finally, this methodology allows us to control the number of COVID-19 cases over time.

The second robustness checks run our primary model for different time windows (every two hours), focusing on the COVID-19 effect/change (α_{1i}) on Travel distance variable over time. This allows us to exploit the increased variability of daily bike trips. It also shows the most important time windows to understand the user's profile or why people use bicycles (for instance, work, leisure, etc.). This is useful since we cannot distinguish between those BSS trips that serve as the first/last mile to public transport and those that are used to commute or go to school.

[21] VTCs are private companies whose vehicles (e.g., cars, minivans, and limousines) do not have a cab sign on the roof or a meter inside and can only accept passengers if a reservation has been made in advance. Services are personalized, and a fixed price is decided in advance.

[22] For more details, see <https://www.bbc.com/news/world-europe-54716993>.

Finally, the last robustness check is about ranking the estimates. To this end, we standardize/normalize the continuous regressors.[23] This allows us to identify the most important one on BSS usage.[24] We present the 12 continuous (standardized) variables and 12 categorical/dummy variables,[25] both for the COVID-19 effect (α_{1i}) and the complete post-first confinement effect ($\alpha_{oi} + \alpha_{1i}$) respectively, for the cities of Toulouse and Lyon.

The following section shows the econometric results.

4 Econometric results

4.1 Results for Toulouse

4.1.1 Estimates of O&D-specific regressors

In Table 3 below, we present our Poisson regression for different periods/cohorts for Toulouse. We show the estimates for the O&D-specific regressors only, i.e., Travel distance and Travel time; we present their pre-first lockdown effect (α_{0i}), and their COVID-19 effect (α_{1i}) due to the interaction with the dichotomous variable D.

Table 3: Poisson regression for Toulouse. O&D regressors[26]

VARIABLES	(1) Base Model	(2) Comparison June to December	(3) Comparison June to October	(4) Comparison November to December
Travel distance	-0.0099625***	-0.0101134***	-0.0098720***	-0.0109149***
(Travel distance)*D	0.0025534***	0.0026923***	0.0026607***	0.0026858***
Travel time	0.0017079***	0.0017614***	0.0016507***	0.0033226***
(Travel time)*D	0.0017554***	0.0017019***	0.0019317***	-0.0007689
Constant	0.3263654***	0.4045445***	0.3131891***	0.6717705***
Observations	5,730,162	3,835,058	2,990,104	844,954
Pseudo R-squared	0.000850	0.000863	0.000882	0.000633

Robust standard errors
*** p<0.01, ** p<0.05, * p<0.1

[23] To obtain standardized regressors, each continuous variable is subtracted by its mean and then divided by its standard deviation. Thus, all standardized regressors have zero expected value and variance equal to 1.

[24] The continuous (standardized) regressors and categorical/dummy regressors are ranked from highest to lowest, according to the absolute value of the respective estimator. This applies to the Toulouse (Tables 3.d and 3.e) and Lyon (Tables 3.i and 3.j) results.

[25] For categorical/dummies variables, we have calculated the discrete effect of these variables using the following formula: $[e^{(\beta)} - 1]$; where β is the effect estimated from the Poisson model.

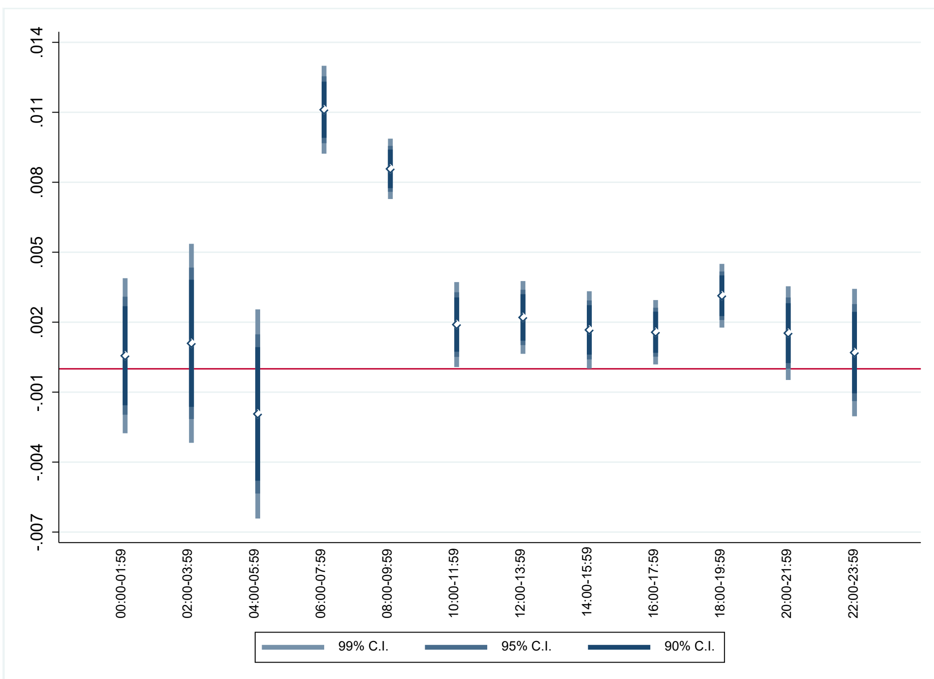
[26] The variables that are left side fitted in Table 3.a represent the pre-1st confinement effect of these variables (α_{oi}), while the centered variables represent the change or COVID-19 effect of these variables (α_{1i}). This layout of variables is maintained in all regressions shown hereafter.

The results confirm our initial predictions. The travel distance regressor has a negative effect before the first lockdown, as an increase of 1 kilometer in travel distance decreases bike trips per hour by approximately 1%, on average.

However, the COVID-19 effect on these variables is positive and significant across all period regressions. The results show that post-first confinement more trips were made per additional kilometer, indicating an increased willingness to travel longer distances post COVID-19 outbreak, likely to avoid social interaction.

Similarly, the travel time variable positively impacts the number of bike trips pre-lockdown, which is an expected result. The COVID-19 effect is also positive in most period regression (except in the fourth one, which is non-significant at 95% confidence), suggesting that users are more willing to spend more time cycling, possibly avoiding faster public transport alternatives.

Graph 10: COVID-19 effect (α_{1i}) on the Travel distance regressor every 2 hours for Toulouse



Graph 10 illustrates the COVID-19 effect (α_{1i}) on the Travel distance variable across different time windows (every 2 hours) in Toulouse. These results show that morning hours, especially between 06:00 and 10:00, mainly drive the change in this regressor post-COVID-19 outbreak. This suggests that people probably use more bikes for commuting or similar purposes in Toulouse (for example, going to school).

4.1.2 Estimates of non-O&D-specific regressors

Table 4 shows the regression results for the non-O&D-specific regressors day of the week (Monday, Tuesday, ...) and type of day (Public holiday, School vacations, Ordinary and Summer)

Related to the day of the week regressors, we observe that weekdays and Saturdays present comparatively fewer trips than the base group (Sunday) before the first confinement. The COVID-19 effect is generally negative and significant, except during the pseudo-normal period (June-October 2020), indicating a temporary return to pre-pandemic biking habits.

The type of day regressors show notable results. The base group is Ordinary day. The COVID-19 effect shows a positive increase in bike trips during Summer, consistent across all regressions. The Ordinary day regressor, instead, shows almost no statistically significant changes, which would be consistent with people post-first confinement keeping their bike use relatively stable as before the pandemic. Finally, the COVID-19 effect on School vacations was omitted due to perfect collinearity.

Table 4: Poisson regression for Toulouse. Non-O&D regressors: day of the week and type of day

VARIABLES	(1) Base Model	(2) Comparison June to December	(3) Comparison June to October	(4) Comparison November to December
Monday	-0.0569996***	-0.0555534***	-0.0509212***	-0.0377356***
Tuesday	-0.0589425***	-0.0571079***	-0.0535001***	-0.0356222***
Wednesday	-0.0588699***	-0.0568455***	-0.0535140***	-0.0379131***
Thursday	-0.0587599***	-0.0568021***	-0.0528172***	-0.0387630***
Friday	-0.0490023***	-0.0474604***	-0.0447670***	-0.0261614***
Saturday	-0.0106857***	-0.0082745***	-0.0077659***	-0.0030454
(Sunday)*D	-0.1456411**	-0.2041921***	-0.0987893	-0.5810122***
(Monday)*D	-0.1530802**	-0.2136924***	-0.1127013	-0.5788403***
(Tuesday)*D	-0.1557375**	-0.2165000***	-0.1152146	-0.5818338***
(Wednesday)*D	-0.1569616**	-0.2177729***	-0.1172826	-0.5770117***
(Thursday)*D	-0.1576260**	-0.2179543***	-0.1187496	-0.5750061***
(Friday)*D	-0.1579842**	-0.2179994***	-0.1154834	-0.5827291***
(Saturday)*D	-0.1532701**	-0.2136833***	-0.1062708	-0.6007841***
Summer	0.0023010*	0.0009873	-0.0006286	
Public holiday	0.0516661***	0.0451462***	0.0406396***	0.0288161***
School vacations	0.0014077**	0.0027664**	0.0010505	-0.0019297
(Summer)*D	0.0081960***	0.0083912***	0.0120975***	
(Public holiday)*D	-0.0122512***	-0.0060342*	0.0040932	-0.0162300**
(Ordinary day)*D	-0.0024794**	-0.0015879	-0.0005504	0.0024132
(School vacations)*D				
Constant	0.3263654***	0.4045445***	0.3131891***	0.6717705***
Observations	5,730,162	3,835,058	2,990,104	844,954
Pseudo R-squared	0.000850	0.000863	0.000882	0.000633

Robust standard errors
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Poisson regression for Toulouse. Non-O&D regressors: public transport system and weather

VARIABLES	(1) Base Model	(2) Comparison June to December	(3) Comparison June to October	(4) Comparison November to December
Outside option	0.0000141***	0.0000128***	0.0000154***	0.0000068***
(Outside option)*D	0.0000014*	0.0000009	0.0000011	0.0000021
Bus users	-0.0000043***	-0.0000039***	-0.0000048***	-0.0000021***
(Bus users)*D	-0.0000005*	-0.0000003	-0.0000002	-0.0000013*
Metro users	-0.0000043***	-0.0000039***	-0.0000047***	-0.0000021***
(Metro users)*D	-0.0000004	-0.0000002	-0.0000003	-0.0000000
Tram users	-0.0000043***	-0.0000037***	-0.0000045***	-0.0000015***
(Tram users)*D	-0.0000008**	-0.0000009**	-0.0000006	-0.0000021
Rain	-0.0050323***	-0.0050759***	-0.0022085***	-0.0145730***
(Rain)*D	0.0038941***	0.0036493***	0.0012779	0.0089090***
Temperature	0.0009843***	0.0006191***	0.0006613***	0.0011206***
(Temperature)*D	0.0006722***	0.0009743***	0.0008256***	0.0008995***
Wind speed	-0.0003890***	-0.0002418**	0.0000489	-0.0013372***
(Wind speed)*D	0.0000003	-0.0002111	-0.0002311	-0.0001564
Solar radiation	-0.0001206***	-0.0001367***	-0.0001383***	-0.0001329***
(Solar radiation)*D	-0.0000524***	-0.0000357***	-0.0000388***	0.0000855***
Constant	0.3263654***	0.4045445***	0.3131891***	0.6717705***
Observations	5,730,162	3,835,058	2,990,104	844,954
Pseudo R-squared	0.000850	0.000863	0.000882	0.000633

Robust standard errors
*** p<0.01, ** p<0.05, * p<0.1

Table 5 presents the regression outputs of the non-O&D regressors related to the public transport system (Bus, Metro, and Tram users), weather (Rain, Temperature, Wind speed, and Solar radiation), and the outside option.

Public transport regressors exhibit negative estimates during the pre-first confinement period (in all public transport systems and all period regressions), which is expected given their substitution to the BSS. However, we observed a statistically significant COVID-19 effect in only one of these regressions, indicating that substitution levels remained constant after the COVID-19 outbreak in Toulouse.

Weather regressors show interesting results. The Rain regressor estimate is negative, as expected. However, the COVID-19 effect is positive and robust in all but the third regression (statistically non-significant). This suggests a higher willingness to use bikes despite unfavorable weather conditions, likely to avoid more congested modes of transportation.

The Temperature variable has a positive and significant effect on bike trips pre-first confinement, which increases post-first confinement (positive COVID-19 effect). These estimates are expected; lower temperatures should discourage bike usage, and a higher sensitivity during the outbreak (positive COVID-19 effect) is likely explained by an aversion to getting sick during the pandemic.

The Solar radiation regressor shows the same expected behavior (a negative estimate on bike trips) since the higher the solar radiation, the lower the number of bike trips are expected to be. This effect increases post-first confinement, which could be explained by what happened to the Temperature variable (the population is more reluctant to face situations that could affect their health post COVID-19 outbreak).

4.1.3 Standardized results

Tables 6 and 7 summarize the top 12 continuous (standardized) and 12 categorical/dummy regressors for Toulouse,[27-28] for the COVID-19 effect (Table 6) and the complete post-first confinement effect (Table 7). All effects are statistically significant, at the 95% confidence level or higher.

Related to the COVID-19 effect on categorical/dummy regressors (Second column in Table 6), the variables for the day of the week (Monday, Tuesday, etc.) stand out. This makes sense; the reduction in general mobility was due to COVID-19 measures, such as teleworking.

The results indicate that those areas where most "households are composed of 1 or 2 people" have experienced an increase in origin and destination trips after the first confinement in France. After COVID-19, people could prefer to travel to areas with fewer residents per household to decrease the contagion probability.

Finally, we observe fewer trips to those areas where most families are "woman with children". A possible explanation could be linked to discrimination against them in the labor market, affecting their employability due to childcare. Another possible explanation could be linked to the fact that women are overrepresented in professions that temporarily could not be performed during the confinement, and it took a while to recover regular customers, such as beauticians, hairdressers, cleaners, or administrative employees, while technical professions such as construction workers, vehicle mechanics, drivers, gardeners, police or firemen were considered essential workers (they never stopped commuting to work) and men are overrepresented in this sector. (See Van der Kloof and Kensmil, 2020.)

Considering the COVID-19 effect on continuous (standardized) variables (first column, Table 6), Travel distance shows a higher willingness to make longer trips since the COVID-19 outbreak. The Temperature regressors also stand out among the most significant changes. Both variables are probably explained by an aversion to getting the virus.

The results indicate a positive COVID-19 change in areas where people are older. A possible explanation is that since age is a risk factor for COVID-19, older people and visitors opted for transport modes with a lower risk of contagion (like the BSS). Although it may seem surprising at first, given the fact that usually, younger people usually tend to bike more, this

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[27] To standardize the regressors, each variable is subtracted by its mean and then divided by its standard deviation. Thus, all standardized regressors have zero expected value and variance equal to 1.

[28] As before, for categorical/dummies variables, we have calculated the discrete effect of these variables using the following formula: $[e^{(\beta)} - 1]$; where β is the effect estimated from the Poisson model.

result goes in line with Hua et al., 2021, who found an increase in bike usage by older people during the pandemic

Finally, with respect to the complete post-first lockdown effects (Table 7), the main variables that explain the use of BSS are those related to public transport, i.e., Bus, Metro, and Tram users, and the outside option variable. These results would indicate that BSS usage is explained more by commuting than leisure trips. In addition, Travel distance and Temperature stand out. Lastly, the Proportion of students is a remarkable variable in explaining traveling to and from specific areas.

Table 6: Main COVID-19 changes (α_{1i}). Top 12 continuous (standardized) and 12 categorical variables for Toulouse

Covid-19 effect (α_{1i})			
Continuous Variable	Standardized effect	Dummy variable	Discrete effect
# Tram users	-0.012	Friday	-0.044
Temperature	0.005	Thursday	-0.044
Solar radiation	-0.005	Wednesday	-0.043
# Resto/Bars at destination	0.005	Tuesday	-0.042
Travel distance	0.004	Saturday	-0.040
# Resto/Bars at origin	0.003	Monday	-0.039
Average age at destination	0.003	Most are 1-person households at destination	0.038
# Health centers at destination	-0.003	Most are 2-people households at destination	0.035
# Banks at destination	-0.003	Most are people with interrupted schooling at origin	0.028
# Pharmacies at destination	0.003	Most are "woman with children" families at destination	-0.020
Travel time	0.002	Most are 1-person households at origin	0.020
# Health centers at destination	-0.002	Most are "childless couples" families at destination	-0.019

Table 7: Main post-first lockdown effects ($\alpha_{oi} + \alpha_{1i}$). Top 12 continuous (standardized) and 12 categorical variables for Toulouse

Complete post 1st confinement effect ($\alpha_{oi} + \alpha_{1i}$)			
Continuous Variable	Standardized effect	Dummy variable	Discrete effect
# Outside option users	0.997	Thursday	-0.059
# Metro users	-0.559	Wednesday	-0.059
# Bus users	-0.384	Tuesday	-0.058
# Tram users	-0.074	Monday	-0.053
Solar radiation	-0.016	Most are students > 14 years old at destination	0.053
Temperature	0.013	Friday	-0.050
Travel distance	-0.011	Most are students > 14 years old at origin	0.045
Student proportion at destination	-0.009	Public holiday	0.039
Student proportion at origin	-0.007	Most are employed at destination	0.029
# Resto/Bars at destination	0.006	Most are people with interrupted schooling at destination	-0.026
# Resto/Bars at origin	0.006	Most are "woman with children" families at destination	0.027
# Banks at origin	-0.006	Most are "only woman" families at destination	0.022

4.2 Results for Lyon

4.2.1 Estimates of O&D-specific regressors

Table 8 presents our Poisson results for Lyon, showing the O&D-specific variables only, i.e., the Travel distance and Travel time variables, as we showed for the Toulouse case.

Table 8: Poisson regression for Lyon. O&D regressors

VARIABLES	(1) Base Model	(2) Comparison June to December	(3) Comparison June to October	(4) Comparison November to December
Travel distance	-0.0271801***	-0.0282142***	-0.0313873***	-0.0186307***
(Travel distance)*D	0.0129295***	0.0139168***	0.0164305***	0.0072185***
Travel time	0.0002826**	0.0006946***	0.0007182***	0.0005782***
(Travel time)*D	0.0001503	-0.0002618	-0.0003180	0.0005935
Constant	0.6748693***	0.8866841***	0.8259683***	0.9023548***
Observations	10,501,968	7,058,847	5,459,370	1,599,477
Pseudo R-squared	0.00171	0.00184	0.00169	0.00265

Robust standard errors
*** p<0.01, ** p<0.05, * p<0.1

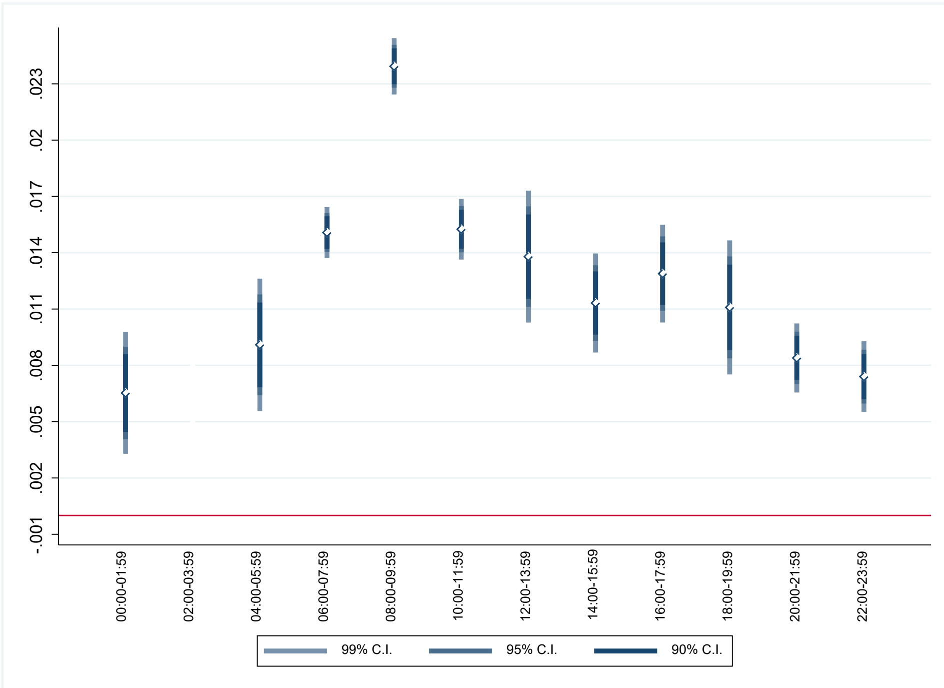
Consistent with Toulouse's results, the Travel distance regressors are negative across all period regressions before the first confinement, indicating that one additional kilometer implies an average reduction of 2%- 3% trips per hour. The COVID-19 effect is also positive and statistically significant at 99% confidence in all cohort regressions, indicating that more trips per additional kilometer were made post-first lockdown.

Unlike Toulouse, the Travel time variable does not show a significant COVID-19 effect; in other words, there is no greater willingness to make longer trips in Lyon after the COVID-19 outbreak, *ceteris paribus*.

Graph 11 depicts the COVID-19 effect (α_{1i}) on the Travel distance regressions and its confidence intervals at 99%, 95%, and 90%, considering different time windows during the day (every two hours) for the city of Lyon.

The data from Lyon reveals a significant pattern, mirroring the findings from Toulouse, where the primary peak hours for increased travel distance are between 08:00 and 10:00. This observation further supports the hypothesis that this shift could be attributed to the growing trend of using the BSS for daily commutes or other related activities, such as school or college runs.

Graph 11: COVID-19 effect (α_{1i}) on travel distance regressor every 2 hours for Lyon



4.2.2 Estimates of non-O&D-specific regressors

Table 9, next, shows the period regressions for the non-O&D-specific regressors day of the week and type of day for Lyon.

The day of the week regressors show that weekdays and Saturdays present fewer trips compared to “Sunday” before the first lockdown. However, in contrast to what was observed for Toulouse, the COVID-19 effect is non-significant in all period regressions except for the third column (June-October). The June-October (pseudo-normal period) results are interesting as they suggest people will use bikes even more than they did before the pandemic.

The type-of-day estimates are similar to those observed for Toulouse. First, we observe a positive estimate for the COVID-19 effect in the Summer. Second, the COVID-19 impact on Public holidays is negative across period regressions, except in the third column (period June-October). Third, the COVID-19 impact on the Ordinary day is non-significant in almost all regressions. This evidence is consistent with the increase in bike usage in Lyon, at least during the pseudo-normal period. Finally, the COVID-19 impact on School vacations was omitted due to collinearity.

Table 9: Poisson regression for Lyon. Non-O&D regressors: day of the week and type of day

VARIABLES	(1) Base Model	(2) Comparison June to December	(3) Comparison June to October	(4) Comparison November to December
Monday	-0.0644691***	-0.0632551***	-0.0639723***	-0.0600889***
Tuesday	-0.0665271***	-0.0661829***	-0.0671812***	-0.0651418***
Wednesday	-0.0673210***	-0.0658210***	-0.0661827***	-0.0653502***
Thursday	-0.0642176***	-0.0631661***	-0.0642023***	-0.0566870***
Friday	-0.0584201***	-0.0570075***	-0.0578012***	-0.0554752***
Saturday	-0.0049143***	-0.0028368	-0.0031347**	-0.0033472
(Sunday)*D	-1.6090161	-1.5623205	1.2197800***	-2.7651410**
(Monday)*D	-1.6131984	-1.5679116	1.2111332***	-2.7554526**
(Tuesday)*D	-1.6123828	-1.5659730	1.2125645***	-2.7480001**
(Wednesday)*D	-1.6151651	-1.5698141	1.2083313***	-2.7522423**
(Thursday)*D	-1.6156322	-1.5696524	1.2092457***	-2.7577534**
(Friday)*D	-1.6131144	-1.5677073	1.2113926***	-2.7528439**
(Saturday)*D	-1.6076436	-1.5628042	1.2166554***	-2.7559185**
Summer	-0.0141988***	-0.0131469***	-0.0153322***	
Public holiday	0.0666435***	0.0615837***	0.0306978***	0.0978741***
School vacations	-0.0026323***	-0.0053701*	-0.0090813***	0.0107484
(Summer)*D	0.0197460***	0.0131082***	0.0117921***	
(Public holiday)*D	-0.0303312***	-0.0287543**	0.0066973	-0.0616420*
(Ordinary day)*D	0.0018164	-0.0022658	-0.0028399*	0.0003543
(School vacations)*D				
Constant	0.6748693***	0.8866841***	0.8259683***	0.9023548***
Observations	10,501,968	7,058,847	5,459,370	1,599,477
Pseudo R-squared	0.00171	0.00184	0.00169	0.00265

Robust standard errors
*** p<0.01, ** p<0.05, * p<0.1

Table 10 shows the results of the non-O&D-specific regressors for public transport modes, weather, and the outside option. We observe negative estimates for the public transport regressor during the pre-first lockdown period (across transport systems and all period regressions), as we did for Toulouse. This is expected given the substitution between the different transport modes. However, in contrast to what was observed in the Toulouse regressions, we see positive estimates for COVID-19 impact across all public transport systems and in almost all regressions (except the fourth one). This suggests that, after the COVID-19 outbreak, public transport (Bus, Metro, and Tram) in Lyon was less of a substitute for people who use the BSS. This would make sense given the population's aversion to using congested transport systems to reduce the virus spread.

Weather regressors have some results similar to those of Toulouse. COVID-19 impact on the Rain variable is statistically non-significant. The COVID-19 effect on Temperature aligns with what was observed for Toulouse, with a positive and significant estimate in almost all regressions (except the fourth regression). It would be consistent with a lower willingness to use bikes in the presence of lower temperatures after the COVID-19 outbreak, probably to avoid situations that may affect health.

The Solar radiation regressor presents a negative COVID-19 effect across all regressions, consistent with people avoiding high-risk health situations after the COVID-19 outbreak.

Finally, the COVID-19 impact on Wind speed is mixed, showing a positive estimate in the first regression (Base model) but a negative estimate in the third regression (pseudo-normal period).

Table 10: Poisson regression for Lyon. Non-O&D regressors: public transport system and weather

VARIABLES	(1) Base Model	(2) Comparison June to December	(3) Comparison June to October	(4) Comparison November to December
Outside option	0.0001264***	0.0001122***	0.0001038***	0.0001845***
(Outside option)*D	-0.0000416***	-0.0000282***	-0.0000231***	-0.0000094
Bus users	-0.0000372***	-0.0000332***	-0.0000307***	-0.0000538***
(Bus users)*D	0.0000116***	0.0000081***	0.0000065***	0.0000019
Metro users	-0.0000381***	-0.0000335***	-0.0000312***	-0.0000547***
(Metro users)*D	0.0000112***	0.0000068***	0.0000053***	0.0000010
Tram users	-0.0000417***	-0.0000373***	-0.0000344***	-0.0000635***
(Tram users)*D	0.0000156***	0.0000113***	0.0000097***	0.0000065
Rain	-0.0022969***	-0.0030110***	-0.0024985***	0.0020523
(Rain)*D	0.0008356	0.0011057*	0.0007268	-0.0052495
Temperature	0.0006908***	0.0001092	0.0003820***	0.0005841
(Temperature)*D	0.0010051***	0.0012836***	0.0008567***	0.0000469
Wind speed	-0.0004318***	0.0003193*	0.0006489***	-0.0011000
(Wind speed)*D	0.0004258***	-0.0001813	-0.0004038**	0.0013290*
Solar radiation	-0.0000327***	-0.0000523***	-0.0000695***	0.0001435*
(Solar radiation)*D	-0.0000652***	-0.0000455***	-0.0000308***	-0.0001426*
Constant	0.6748693***	0.8866841***	0.8259683***	0.9023548***
Observations	10,501,968	7,058,847	5,459,370	1,599,477
Pseudo R-squared	0.00171	0.00184	0.00169	0.00265

Robust standard errors
*** p<0.01, ** p<0.05, * p<0.1

4.2.3 Standardized results

Tables 11 and 12 provide the main 12 continuous (standardized)[29] and 12 categorical/dummy variables for Lyon; their COVID-19 effects, and complete post-first confinement estimates, respectively. All these effects are statistically significant at the 95% confidence level or higher.

[29] To standardize the regressors, each variable is subtracted by its mean and then divided by its standard deviation. Thus, all standardized regressors have zero expected value and variance equal to 1.

Table 11: Main COVID-19 effects (α_{1i}). Top 12 continuous (standardized) and 12 categorical variables for Lyon

Covid-19 effect (α_{1i})			
Continuous Variable	Standardized effect	Dummy variable	Discrete effect
# Outside option users	-0.465	Most are 'woman with children' families at destination	-0.719
# Metro users	0.174	Most people walk to work at origin	-0.052
# Bus users	0.170	Most are 'couple with 2 children' families at origin	-0.040
# Tram users	0.114	Most are 'only man' families at origin	-0.039
Travel distance	0.021	Most are families with 1 car at origin	0.036
Temperature	0.008	Most are employed at origin	-0.030
Solar radiation	-0.006	Public holiday	-0.030
Women proportion at origin	-0.006	Most are 'childless couples' families at origin	-0.029
Foreigners proportion at origin	-0.005	Most are families without cars at origin	0.028
# Resto/Bars at origin	0.004	Most are 'couple with 2 children' families at destination	-0.026
Average age at origin	0.004	Most are 'only man' families at destination	-0.023
Student proportion at origin	-0.004	Most are 'childless couples' families at destination	-0.022

Table 12: Main post-first lockdown effects ($\alpha_{oi} + \alpha_{1i}$). Top 12 continuous (standardized) and 12 categorical variables for Lyon

Complete post 1st confinement effect ($\alpha_{oi} + \alpha_{1i}$)			
Continuous Variable	Standardized effect	Dummy variable	Discrete effect
# Outside option users	0.949	Most are 'only woman' families at destination	0.049
# Metro users	-0.407	Most people walk to work at destination	0.045
# Bus users	-0.384	Most are 'only man' families at destination	0.042
# Tram users	-0.192	Most are 'only woman' families at origin	0.040
Travel distance	-0.023	Public holiday	0.040
Temperature	0.014	Most have '3-4 years of post-secondary education' at destination	0.035
Women proportion at origin	-0.011	Most are 'childless couples' families at destination	0.033
Solar radiation	-0.009	Most people walk to work at origin	0.033
Women proportion at destination	-0.009	Most are 'only man' families at origin	0.030
Average age at origin	0.007	Most are executives and professionals at origin	0.029
# Health centers at destination	0.006	Most are 'childless couples' families at origin	0.028
Average age at destination	0.005	Most are laborers at destination	-0.026

Regarding the standardized continuous regressors (first column, Table 11), the public transport variables stand out. The variables Bus, Metro, and Tram users present a positive COVID-19 estimate, which implies a decrease in substitutability to the BSS in Lyon. In addition, as seen in Toulouse, the variables Travel distance and Temperature are relevant, showing a higher willingness to have longer trips and a lower propensity to travel in low temperatures since the COVID-19 outbreak. Similarly, the "Average age" regressor again highlights having a positive COVID-19 impact on origin bike trips. This finding is interesting since older people probably use more bikes than before the pandemic to reduce virus contagion (age is a risk factor for COVID-19). As we said before, this result aligns with Hua et al. 2021, who found an increase in bike usage by older people during the pandemic.

Another interesting result is related to the “women proportion” regressor. The result states that after the COVID-19 outbreak, fewer trips are observed from areas with proportionally more women. One potential explanation could be related to discrimination against women, for instance, in the labor market, staying more at home due to the health crisis. As we said before, women are overrepresented in professions that were forbidden to perform during confinement, taking a while to recover afterward. For example, Van der Kloof and Kensmil (2020) found that COVID-19 measures had a greater negative effect on mobility for women than for men since the proportion of women staying at home or out of work (21%) during the pandemic was more than double than that of men (10%) in the Netherlands.

On the other hand, the main COVID-19 impacts on categorical/dummy regressors are related to demographic variables (second column, Table 11). First, the variable “woman with children” stands out. This variable indicates that, since the COVID-19 outbreak, there has been a reduction in the number of trips to areas where most families are women and children only. Once again, this variable may indicate some employment bias or discrimination against women.

Likewise, “household family” regressors show that the impact of COVID-19 was rather general, showing no bias towards a specific family structure, except for the one explained above ("women with children" families). The regressor "families without cars" stands out; in those areas where the majority are families without cars, there has been an increase in bike use since the COVID-19 outbreak.

Finally, there are some interesting results regarding the post-first confinement estimates (Table 12). As in Toulouse’s case, in Lyon, the main variables explaining the use of BSS are related to public transport, which shows the degree of substitution among these transport modes. Likewise, the Travel distance and Temperature variables again stand out, as in Toulouse's case.

5 Policy implications and conclusions

The econometric and descriptive evidence provide robust and interesting findings. The first remarkable result is the increase in travel distance using BSS. For both cities (Toulouse and Lyon), a clear increase is observed in the Travel distance estimate after the COVID-19 outbreak, which is statistically significant at 99% confidence and robust across period regressions. These findings have been consistent across all our checks and are likely permanent.

The time-slot analysis (every 2 hours) on the Travel distance variable showed that the increase in travel distance is at the beginning of the working day. This evidence suggests that the change in travel distance would be mainly explained by people who use bikes to commute or similar activities (such as going to university).

On the other hand, the period regressions show a mixed recovery in bike usage after the first confinement, especially in the June-October cohort (pseudo-normal period). Indeed, in

Toulouse during the pseudo-normal period, there is no statistically significant change between bike trips before and after the first confinement in France. In the case of Lyon, June-October shows an increase in bike trips with respect to the pre-first confinement period, which is statistically significant at 95% confidence. In our opinion, these results show the resilience of the BSS in these cities, especially in Lyon, where we can see an increase in bike trips.

The weather regressors also present salient results. In the case of Toulouse, after the COVID-19 start, there is a generally lower sensitivity to Rain, while there is no statistically significant change in the Wind speed variable. In the case of Lyon, we see a mixed COVID-19 impact on Wind speed and a lower sensitivity of Rain only in the June-December cohort. Likewise, a greater temperature sensitivity is observed for both cities. This evidence would indicate a higher willingness to use bikes in adverse climatic situations (more rain and wind), probably due to avoiding public transport.

Finally, although not all the results coincide between Toulouse and Lyon, the standardized regressions provide interesting findings for both cities. First, the regressor Average age shows positive COVID-19 estimates for both cities. This is expected as age is a risk factor for COVID-19. It follows that visitors and older people prefer to use a transport mode with a lower risk of contagion, such as the BSS.

Similarly, changes in the Travel distance and Temperature regressors in Toulouse and Lyon stand out. This evidence shows an important change in people's habits after the COVID-19 outbreak, as they would be willing to ride longer distances and avoid low temperatures.

Another remarkable regressor in Toulouse and Lyon is "woman with children". Indeed, the evidence shows a decrease in trips in those areas where women with children are the majority. In this regard, a potential explanation could be some discrimination in the labor market against them, which affects their employment.

Likewise, especially in Lyon, the variable "women proportion in each area" is noteworthy. The evidence shows that, after the first confinement, fewer bike trips were made from areas where more women live. The reasons may be various, but in principle, we think some discrimination in the labor market made them end up at home more than men.

Finally, it is noteworthy that the main variables that explain the post-first confinement effect are related to public transport (Bus, Metro, and Tram users), showing the substitutability with the BSS for both cities.

The present study provides worthwhile information about changes in BSS users' behavior, which have the potential to be permanent. It is relevant as it is generally difficult to change users' habits (due to switching costs). However, as the population has already made some changes in favor of cycling due to COVID-19 (these changes are already sunk costs), any public policy in this system starts with an advantage. Thus, our main message is that today, we have an excellent opportunity to start thinking about public policy in this area, seeking to materialize the positive observed changes and thus promote more widespread and permanent adoption of bikes.

In this regard, potential public policies relate to adding technology to BSS in both cities. Indeed, given that people would be traveling longer distances for longer periods and are mainly motivated by commuting, it would be desirable to have a timer to control the time better and thus optimize the restriction of free minutes per trip.[30] This could be easy to implement.

Likewise, in both cities, it would be desirable to have lighter bicycles and an electric version (specifically for Toulouse) to promote its use by people who, although considering BSS as an alternative, may not be using it due to physical disabilities or other reasons. In this scenario, the possibility of having electric bicycles becomes even more important, especially in Toulouse, as evidence shows that older people are making more trips on BSS than before.

The main reference in France is the BSS "Vélib'-Metropole" in Paris. Bikes there are lighter, have timers and have electric versions, which are indeed designed for a larger city that, on average, has longer trips. Thus, the observed changes in bicycle usage after the COVID-19 outbreak are good reasons to seriously evaluate the investment in technology in the BSS of Toulouse and Lyon.

In addition, BSS has traditionally been the widespread option for low-income users; it has been developed as a potential alternative to more polluting means of transport, such as cars or buses. We believe that public investment on BBS goes in line with the Green Deal objectives for 2050 in Europe. For that purpose, it would be desired that local government and transport authorities invest in biking infrastructure (bike lanes and safe parking for bikes) and advertise bike-sharing for the demand unawares of its advantages.[31]

We also support the idea of integrating BSS with other means of transport, as Shaheen *et al.* proposed in 2010. This could be a starting point to facilitate joint use of different transportation means and promote the use of BSS for longer-distance trips in combination with bus or tram.

In order to take into account principles of equality and fairness, we also see a potential for the development of BSS in less dense areas or suburbs, given the persistent high concentration of BSS only in main cities. This idea had already been proposed in 2014, but it has not yet taken place due to the lower profitability of investing in those areas. (See Cohen and Kietzmann, 2014.)

Finally, one potential limitation of this paper is whether the BSS accurately represents or characterizes bike usage in a broader context. Despite acknowledging that BSS only captures a small segment of overall bicycle usage, we believe that by analyzing it, we obtain a reasonable understanding of trends on a more general level. To address this limitation, future research could explore making the functional form of the model more flexible, allowing for the examination of non-linear effects of variables such as travel distance or

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[30] At the Toulouse (VélÔToulouse) and Lyon (Vélo'V) BBSs, the annual plans consider a free minute window of 30 minutes per trip. For more details, visit: <https://abo-toulouse.cyclocity.fr/Comment-ca-marche/Les-velos-stations/Le-service2> and <https://velov.grandlyon.com/en/offers/groups/list#180>

[31] Nikiforiadis et al., 2020 mentioned the difficulty of attracting new users to BSS when they did not have previous experience with them.

travel time. Additionally, gathering additional data, such as average wages by area, could provide insights into how COVID-19 affects individuals differently based on their socioeconomic status.

Responses to reviewers

- We have corrected a typo in the manuscript title, updated and completed the literature review, reviewed the paper for grammatical errors, numbered equations, and verified the origin and destination symbols.
- We have retained the current limit of 7 decimals instead of reducing it to 3 decimals as proposed. This decision reflects the small scale of our estimates, particularly those related to bus, metro, and tram data. We have reserved 3 decimals solely for standardized estimates in tables 6-7 and 11-12.
- COVID-19 deaths are now depicted in graphs 1 and 2.
- We have clarified and explained that we estimate all the parameters simultaneously for each city, respectively.
- The conclusions and policy implications have been further elaborated.
- Appendix B now includes graphs B.1 and B.2 illustrating public transport usage in Toulouse and Lyon, respectively.
- Additional background on Bike-Sharing Systems (BSS) in each city has been included.
- We have clarified in the manuscript that while we are unable to differentiate between first/last mile transit trips and those for work/school commutes, our control for various zone activities accounts for trip purposes.
- Despite attempts to consolidate the presentation of results for Toulouse and Lyon, we found that tables became cumbersome and less reader-friendly. Consequently, results are presented separately by city, acknowledging that this may impact readability.
- Lastly, it should be noted that there were no specific city-level restrictions in France; all measures were centrally coordinated and monitored by the national government.

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Appendix A

The outside option variable is calculated from travel data in BSS and public transport data (Bus, Metro, and Tram). Formally, we have the following:

$$S_t = L_t - (\lambda_t + Bus_t + Metro_t + Tram_t) \tag{3}$$

$$where\ S_t\ is\ the\ Outside\ Option, and\ L_t\ is\ the\ market\ size$$

Since we do not know the total market size, we define it as a function of the number of trips on BSS and public transport (Bus, Metro, and Tram). Formally:

$$L_t = \beta(\lambda_t + Bus_t + Metro_t + Tram_t) \tag{4}$$

$$with\ \beta > 1$$

Finally, from (3) and (4), we obtain the following formula for the outside option variable for each period t.

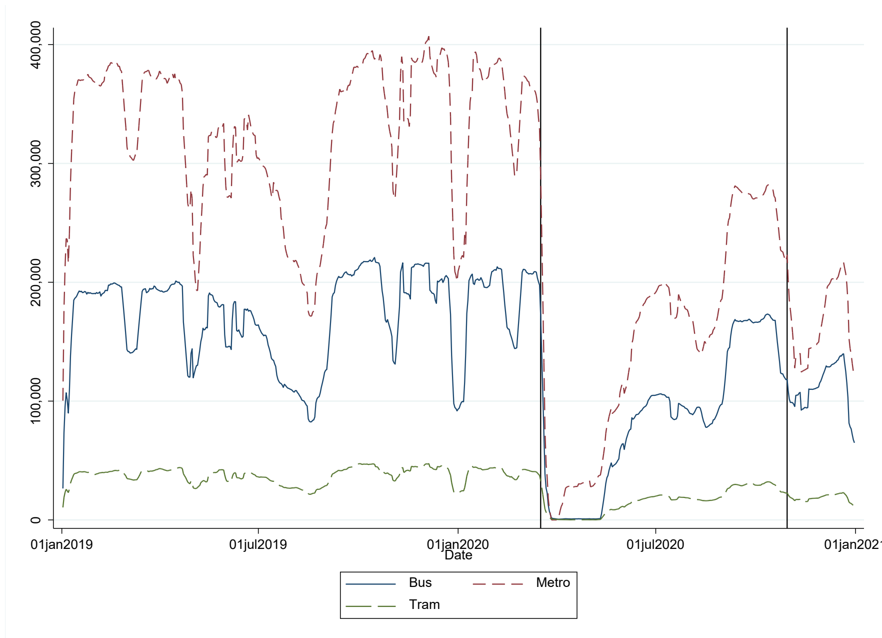
$$S_t = (\beta - 1)(\lambda_t + Bus_t + Metro_t + Tram_t)$$

Finally, we obtain the following formula for the outside option variable for each period t.

In the specific case of Toulouse and Lyon, we have assumed that $\beta = 1.3$. However, the results are robust to different values of β. Also, in the case of Toulouse, the outside option variable is daily, while for Lyon the variable is hour-day.

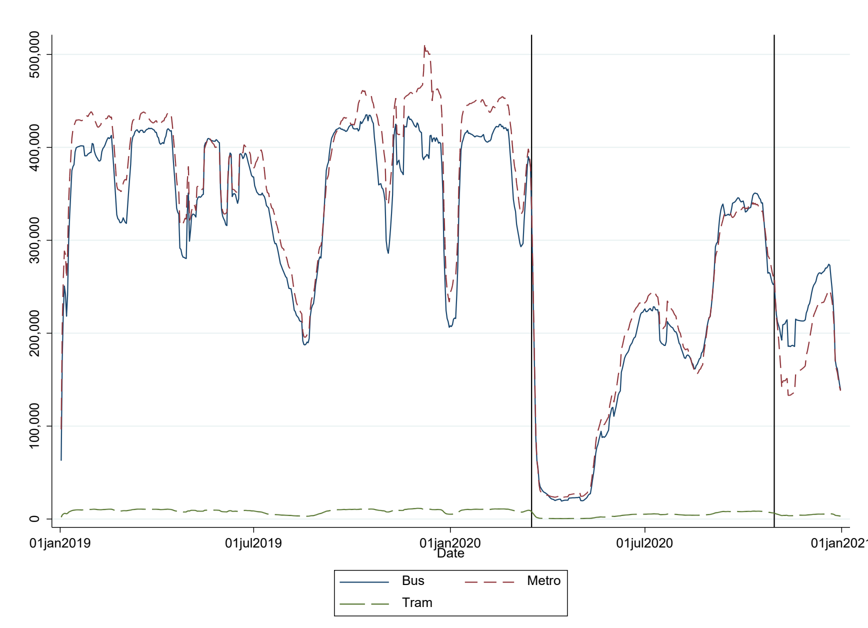
Appendix B

Graph B.1: Public Transport Usage in Toulouse



Note: Black vertical lines refer to the start of the first and second lockdown periods in France. Data is filtered by a 7-day moving average.

Graph B.2: Public Transport Usage in Lyon



Note: Black vertical lines refer to the start of the first and second lockdown periods in France. Data is filtered by a 7-day moving average.

Appendix C

The description of the original categories is in French in the document "Accéder à la liste des variables (pdf)," which is available on the website:

<https://www.insee.fr/fr/statistiques/4802064?sommaire=4508161&q=iris+toulouse#dictionnaire>

The description of the categorical variables in English is given below.

1. Indicator of highest education level

01	No schooling or stopped before the end of elementary school
02	No degree and schooling interrupted at the end of elementary school or before the end of college
03	No diploma and schooling to the end of college or beyond
11	CEP (primary school certificate)
12	BEPC, elementary certificate, college certificate, DNB
13	CAP, BEP or equivalent diploma
14	General or technological baccalaureate, higher diploma, law degree, DAEU, ESEU
15	Professional baccalaureate, vocational, technical or teaching certificate, equivalent diploma
16	BTS, DUT, Deug, Deust, health or social diploma of Bac+2 level, equivalent diploma
17	Licence, licence pro, master's degree, equivalent diploma at bac+3 or bac+4 level
18	Master's degree, DEA, DESS, grande école diploma at bac+5 level, health doctorate
19	Research doctorate (excluding health)
ZZ	Out of field (less than 14 years old)
YY	Not in main residence

2. Indicator of the number of people living in the household

1	One person
2	2 people
3	3 people

4	4 people
5	5 people
6	6 people or more
Z	Outside regular housing

3. Household family structure indicator

11	Person living alone: male
12	Person living alone: woman
21	Main single-parent family without isolation: man with child(ren)
22	Main family without single parent: woman with child(ren)
30	Main family a couple without a single person without children
31	Main family a couple without isolated with 1 child
32	Main family a couple without isolated with 2 children
33	Main family a couple without isolated with 3 children
34	Main family a couple without a single parent with 4 or more children
40	Main family a single parent with one or more children
51	Main family a couple without children with isolated all ascendant(s) or descendant(s)
52	Main family one childless couple with other isolated(s)
53	Main family a couple with child(ren) with isolated all ascendant(s) or descendant(s)
54	Main family one couple with child(ren) with other isolated(s)
61	Two families with or without single person(s): two couples with or without children
62	Two families with or without isolated(s): other cases
70	Other household without family
ZZ	Outside regular housing

4. Indicator of the most used mode of transportation to work

1	No transportation
2	Walking (or rollerblading, skating)
3	Bicycle (including electric)

4	Motorized two-wheeler
5	Car, truck, van
6	Public transportation
Z	Not applicable

5. Indicator of the number of vehicles in the household

0	No car
1	One car
2	Two cars
3	Three or more cars
X	Unoccupied regular housing
Z	Not in regular housing

6. Indicator of the type of activity performed by the person

11	Employed, including apprenticeship or paid internship.
12	Unemployed
21	Retired or pre-retired
22	Pupils, students, unpaid trainees aged 14 or over
23	Less than 14 years old
24	Housewives or men
25	Other inactive

7. Indicator of the person's socio-professional category

1	Farmers
2	Craftsmen, shopkeepers and company managers
3	Executives and higher intellectual professions
4	Intermediate professions
5	Laborers
6	Workers

7	Retired
8	Other people without professional activity