WORKING PAPERS

N° 1317

October 2022

"Covid-19 impact on Bike-sharing systems: An analysis for Toulouse, Lyon, and Montreal"

Marc Ivaldi and Walter Núñez

Toulouse School of Economics

Covid-19 impact on Bike-sharing systems: Lessons from Toulouse, Lyon, and Montreal[1]

Marc Ivaldi[2] Walter Núñez[3]

October 17, 2022

Abstract

Based on Bike-sharing system (BSS) data for Toulouse, Lyon, and Montreal, we study the Covid-19 impact on relevant variables of BSS use. Our results show significant changes related to longer travel distance, which would be explained by those users who use the BSS at peak hour. Also, after Covid-19 outbreak, there is evidence about higher willingness to use the BSS in adverse weather conditions (such as rain and wind), lower substitution with the public transport system in Lyon, and a recovery and even a slight increase of BSS trips for Toulouse and Lyon respectively. In our opinion, these results have the potential to represent permanent changes in user' habits, being an excellent opportunity to make specific investments in this system and thus strongly promote the bicycle use and its permanence.

Keywords: Bike-sharing system, Covid-19 effects, long-term changes.

JEL Classification: R40, L91.

---

[1] This research is partly funded by the ANR projects ANR-21-COVR-0027-01, https://blogs.univ-tlse2.fr/velo/. We thank Bertrand Jouve and researchers of the TRANSITION-VELO for useful insights and comments. Finally, we thank JC Decaux and Tisseo Collectivité for making the data available to us.

[2] Toulouse School of Economics. E-mail: marc.ivaldi@tse-fr.eu

[3] Toulouse School of Economics. E-mail: walter.nunez.1990@gmail.com

1 Introduction

The Covid-19 pandemic has been a huge challenge for the world's population, requiring enormous public health efforts. This has motivated governments to take different measures to contain the Covid-19 spread, which, although having a health focus, have impacted various economic sectors, like transport, by establishing traffic restrictions, international flight limitations, among other measures.

Regarding the transport sector, its relevance for many cities has been counterbalanced by its inadequacy in containing the Covid-19 spread, motivating many people to evaluate different transport options to minimize the contagion likelihood. In this sense, bicycles are presented as a flexible alternative, which allows an efficient and environmentally friendly mobilization, but above all compatible with the health crisis. In this sense, the main objective of this paper is to help in the understanding and analysis of what has happened with the BSS use after the Covid-19 outbreak, in order to provide inputs for the development of public policies in this area

The development of the BSS has been an option with a positive impact on bicycle use in many cities.[4] For example, in Lyon, after the introduction of its BSS (called Velo'v), there was a 44 percent increase in bicycle trips after one year, with 2 million trips in the first 6 months after its introduction, replacing 150,000 car trips (Bührmann, 2007). Additionally, since the launching of the BSS (named Vélib') in Paris, in just one year the system grew to 16,000 bikes and 1,200 stations, making an average of 75,000 trips per day (Luc, 2008). Also, two-thirds of Vélib' users say that BSS trips are usually part of a longer trip, and 1 in 5 users would drive less than before (see Luc (2008)).

Although BSS is not a recent system[5], the economic literature is relatively scarce about the BSS changes since Covid-19 start. For example, in Zurich after the Covid-19 outbreak the statistical analysis reveals that passengers would use the BSS for longer time and distance trips than before (see Li, Zhao, He, & Axhausen (2020)). Another recent study for Beijing by Chai, Guo, Xiao, & Jiang (2020) shows that, overall, BSS trips would have been reduced by 64.8%, followed by an increase of 15.9%, suggesting that productive and residential activities have just been partially recovered. On the other hand, a study for New York by Teixeira & Lopes (2020) shows that the BSS has been more resilient than the subway system, with a less significant drop in the number of users (BSS dropped of 71% versus the 90% dropped of the subway system) and an increase in the average trip duration (from 13 to 19 minutes per trip).

[4] Shaheen, Guzman, & Zhang (2012); Eren & Uz (2020)

[5] On BSS, see Ricci (2015), Fishman (2020), Shaheen, Guzman, & Zhang (2012), and Eren & Uz (2020).

In this sense, and assuming that people have been forced to modify their transports habits in favor of less risky services, such as bicycles, it is interesting to question how these habits are being modified after Covid-19 outbreak and whether they will be permanent. The answers to these questions are tremendously relevant considering the difficulty to change people habits, being an excellent opportunity to carry out a proper diagnosis to evaluate public policies that permanently promote this transportation mode that is more environmentally friendly, compatible with the current pandemic and the health objectives of society. [6]

In this framework and taking into account the challenges and opportunities that may arise from the current pandemic, this work consists of quantifying, using econometric tools, the effect of key variables that impact the BSS use and to see if these effects change after the Covid-19 start. The analysis focuses on three cities: Toulouse and Lyon in France, and Montreal in Canada, where we look at their similarities and contrasts.

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, Lyon, and Montreal. Finally, Section 5 presents the conclusions and policy implications.

2 Data and descriptive analysis

2.1 Data sources

In this section we describe the different databases and sources of information. For the cities of Toulouse and Lyon, we have the following information.

- The main dataset about BSS trips was delivered by the firm JC Decaux, which provided each BSS trip during 2019 and 2020 with its start-end time (format date-hour-minute) and its origin and destination bike stations (O&D[7]). For Toulouse we have 6.943.375 observations, whereas for Lyon we have 15.586.007 observations.

[6] Replies to these questions have been also proposed by Rocci (2015), and Moro, Imhof, Fettermann, & Cauchick-Miguel (2018).

[7] O&D means an origin and destination trip between 2 specific bike stations, directionally.

- Data on weather conditions are obtained from MeteoFrance.[8] We focus on the following 4 variables because of their relevance for the BSS use: (i) Rain (in milliliters), (ii) Wind speed (in meters per second); (iii) Temperature (in degrees Celsius); and (iv) Solar radiation (measured in Joules/CM^2). This information is disaggregated at day-hour level during 2019 and 2020, respectively.

- We have data on validated tickets of people using public transport in Toulouse and Lyon, i.e., Bus, Metro and Tram. The information for Toulouse was provided by Tisséo Collectivité, while Lyon data was delivered by Sytral. In Toulouse case the information is daily, while for Lyon the data is at hour-day level, both for each day during 2019 and 2020.

- To get demographic data on each city, we use information from the French census of 2017.[9] Demographic data are disaggregated at IRIS level (hereinafter referred to as "IRIS area", or just "area"), having several variables to characterize each anonymous person in that area.[10] For example, we can know how many people live in each area, the gender of each person, whether they are employed or studying, the economic sector in which each person works, the educational level of each individual, etc.

- Finally, the last important source of information is the database "permanent equipment base" (BPE).[11] The BPE is a statistical source that provides information about different services in each area during 2019. For example, with this dataset we know the number of restaurants, universities, police stations, health centers, pharmacies, gyms, museums, etc. in each area, for both cities.

Additionally, using these databases, it is possible to obtain additional variables. First, we have the coordinates (latitude and longitude) of each bike station. This is very useful because we could obtain: (i) the travel distance between bike stations; and (ii) the type of area where each bike station is located.[12] To calculate the travel distance,

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

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

[10] The IRIS is a 9-digit numeric code, which represent a homogeneous infra-municipal division of the territory, 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>

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

[12] 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>

we use an open-source provider (HERE), being able to obtain the distance (in kilometers) that a car would follow between bike stations. In addition, as we have information about the start-end time of each BSS trip, we were able to calculate the travel time (in hours) of each trip.[13]

Also, based on public transport data and BSS trips, we create an outside option variable as a proxy for the other transport modes that we cannot observe in our model, such as car or walking.[14] Finally, from the public transportation database, we have information about the day of the week (Monday, Tuesday, etc.) and type of day in France (Public holiday, School vacations, Ordinary and Summer) during 2019 and 2020.[15-16-17]

In the case of Montreal, instead, we have much less data. The BSS trip database has 8.862.586 observations, which can be freely obtained from the website of BIXI, BSS provider in Montreal.[18] It follows the same format as before (trips by O&D, and start-end time of each trip), but only between April and November during 2019 and 2020. With this information we calculate the travel time in hours for each trip. Also, we have the coordinates of each BSS station, being able to calculate the travel distance between stations as before. Finally, we have data about the day of the week (Monday, Tuesday, ...) where the trips took place. Unfortunately, we do not have information on weather conditions, demographic variables, and services, as in the case of Toulouse and Lyon.

Finally, the Tables 1, 2 and 3 present statistical summaries on selected variables for Toulouse, Lyon, and Montreal.

---

[13] 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/>

[14] The methodology is explained in Appendix A.

[15] 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.

[16] 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.

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

[18] For more information, visit: <https://bixi.com/fr/donnees-ouvertes>

Table 1: Statistical summaries. Selected variables for Toulouse

VARIABLES	(1) Mean	(2) Standard deviation	(3) Minimum	(4) 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

VARIABLES	(1) Mean	(2) Standard deviation	(3) Minimum	(4) 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

Table 3: Statistical summaries. Selected variables for Montreal

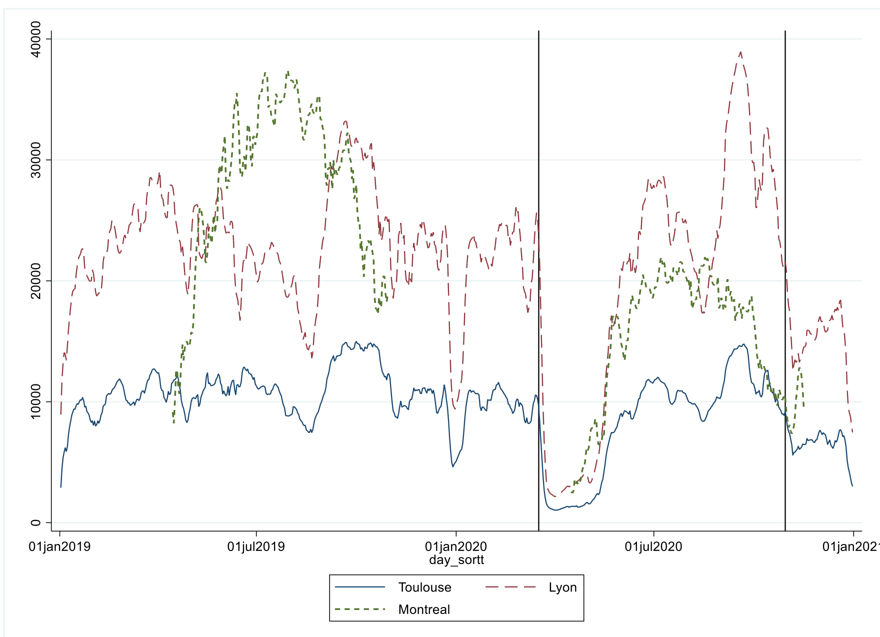
VARIABLES	(1) Mean	(2) Standard deviation	(3) Minimum	(4) Maximum
Travel distance (km.)	2.712	1.965	0	27.538
Travel time (hrs.)	0.238	0.185	0	2

2.2 Descriptive analysis

Let us first view on what happened with the variables of interest, based on trends and density analysis of them. We focus on the variables that could have been directly affected by the first lockdown and "social distancing" measures, such as travel time and travel distance, change in trip start time and change in the BSS use between weekdays.

First, the Graph 1 shows the number of daily trips for the three cities, on a 7-day moving average.

Graph 1: Daily trips for Toulouse, Lyon, and Montreal

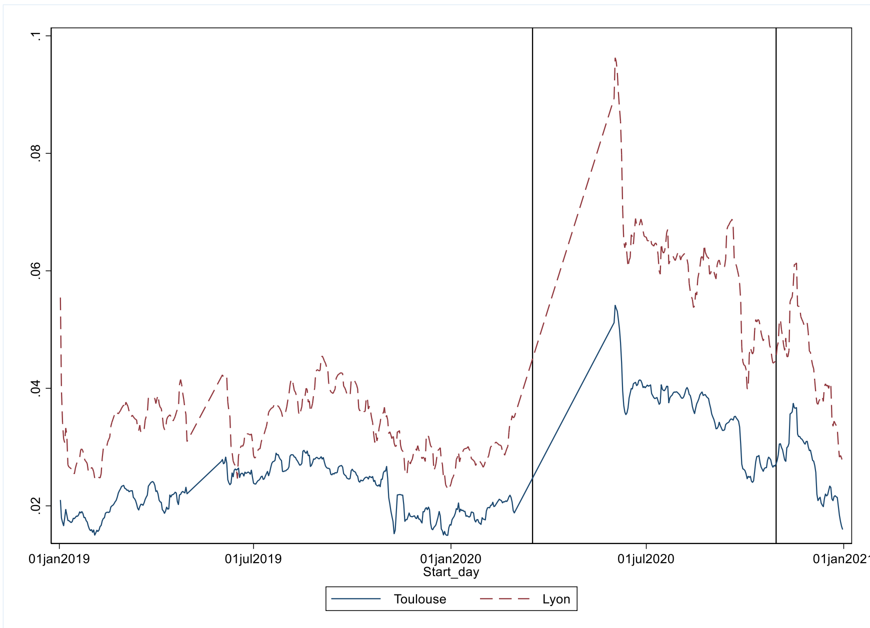


Note: Black vertical lines refer to the start of the first and second lockdown period in France. Data is filtered by a 7-day moving average.

For Toulouse (blue/navy line) and Lyon (red/brown dash line) we observe a sharp decrease in the number of daily BSS trips after Covid-19 outbreak in March (start of the first lockdown). Then, a significant recovery is shown, almost to levels prior to the first confinement, although with more temporal variation and decrease since November 2020 (start of the second lockdown). For the case of Montreal (green short-dash line) we only observe the periods April-November each year, where in 2020 a significant decrease is seen compared to 2019.

Next, the Graph 2 represent the share of BSS daily trips in relation to the daily users of public transport (Bus, Metro and Tram), on a 7-day moving average, for the cities of Toulouse and Lyon.

Graph 2: Daily BSS share over the public transport system for Toulouse and Lyon

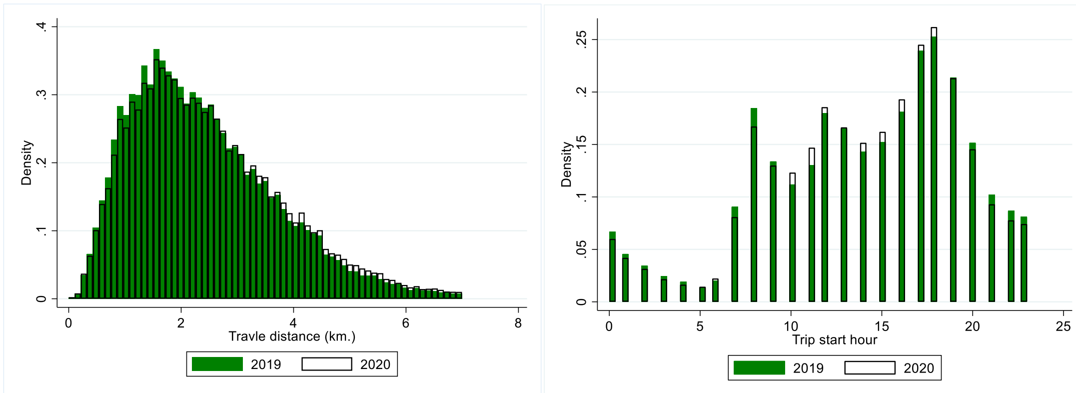


Note: Black vertical lines refer to the start of the first and second lockdown period in France. Data is filtered by a 7-day moving average.

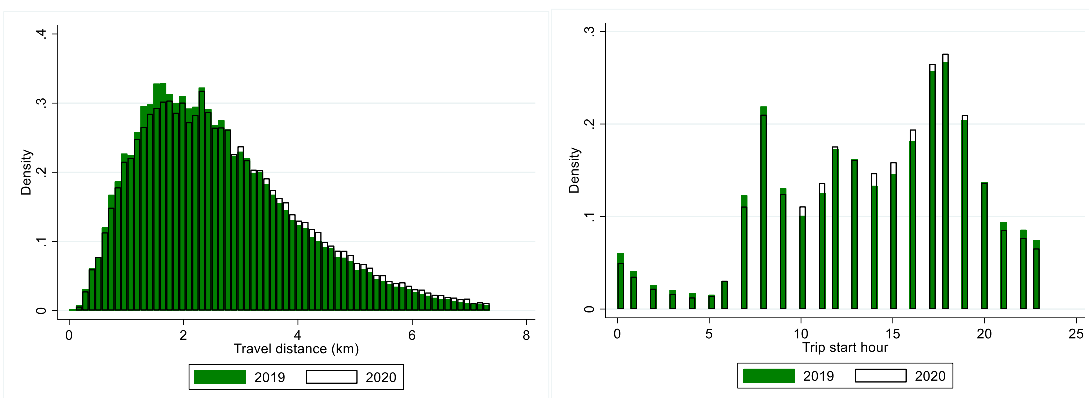
Two important points can be made from this graph. The first is the low relevance of the BSS use in relation to the public transport system, with a share of 1% to 4% approximately. However, the second observation is related to the resilience of the BSS compared to the public transport system. Indeed, after the first lockdown in France, there was a significant jump in the BSS share for both cities, which remained relatively high until almost the beginning of the second confinement in France. These results provide the first insights of a greater intention to use the BSS after the first confinement.

On the other hand, the Graphs 3, 4 and 5 present, for Toulouse, Lyon, and Montreal respectively, the density histogram of travel distance (in kilometers) and trip start hour during 2019 (green bars) and 2020 (transparent bars with black outline).

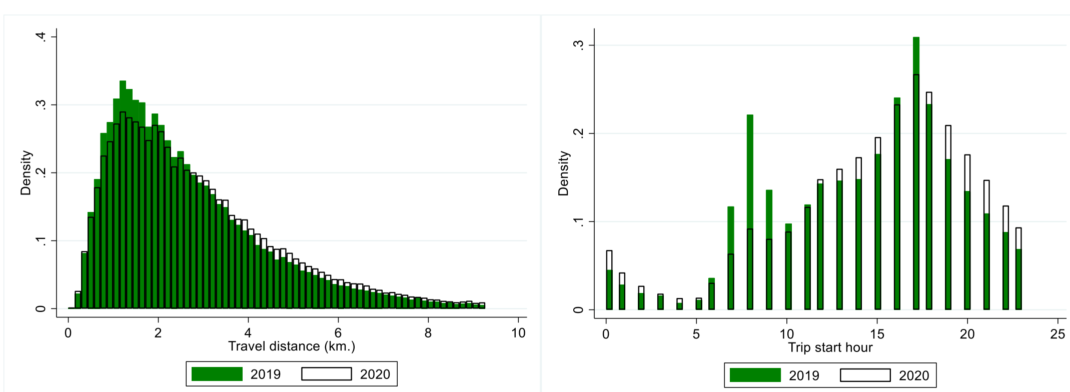
Graph 3: Density histogram of travel distance and trip start hour for Toulouse



Graph 4: Density histogram of travel distance and trip start hour for Lyon



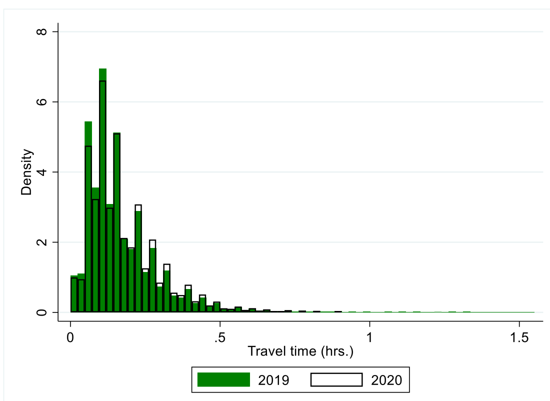
Graph 5: Density histogram of travel distance and trip start hour for Montreal

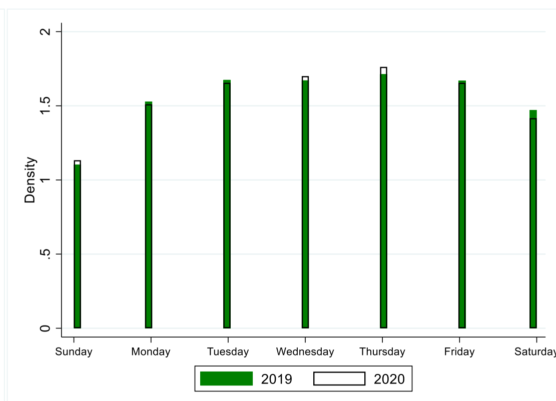


The graphs show a rightward movement in the travel distance density histogram for the three cities in 2020, being more likely to see longer distance trips in 2020 compared to 2019. Regarding the trip start hour distribution, in Toulouse and Lyon the trips were mainly affected by Covid-19 measures, for example curfews, restricting the BSS use mainly between 10:00 and 18:00 hours in 2020. The case of Montreal is different, as it did not have curfew measures during 2020[19]. However, we can see a noticeable decrease during peak hours, such as 07:00 – 09:00 hours and 16:00 – 17:00 hours in 2020, which could be consistent with people's attempt to avoid peak hours.

The Graphs 6, 7 and 8 below show the density histograms of travel time (in hours) and day of week, for 2019 (green bars) and 2020 (transparent bars with black outline), respectively.

Graph 6: Density histogram of travel time and day of week for Toulouse

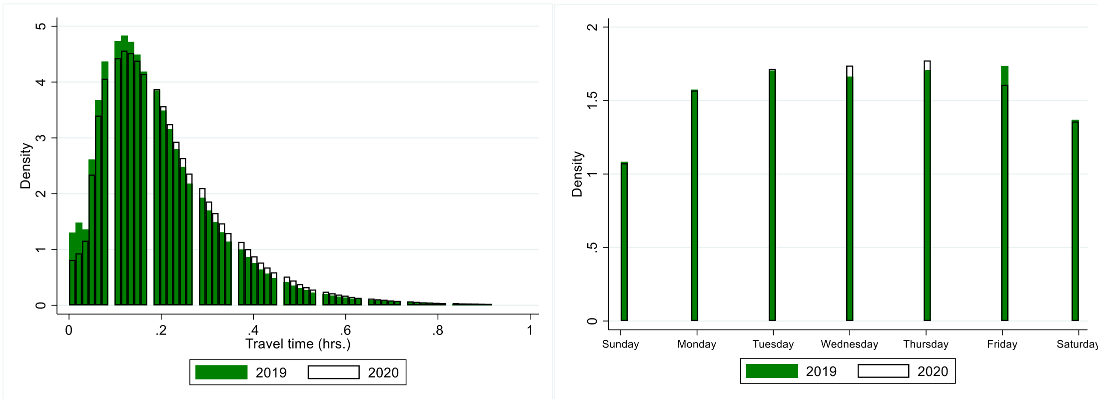




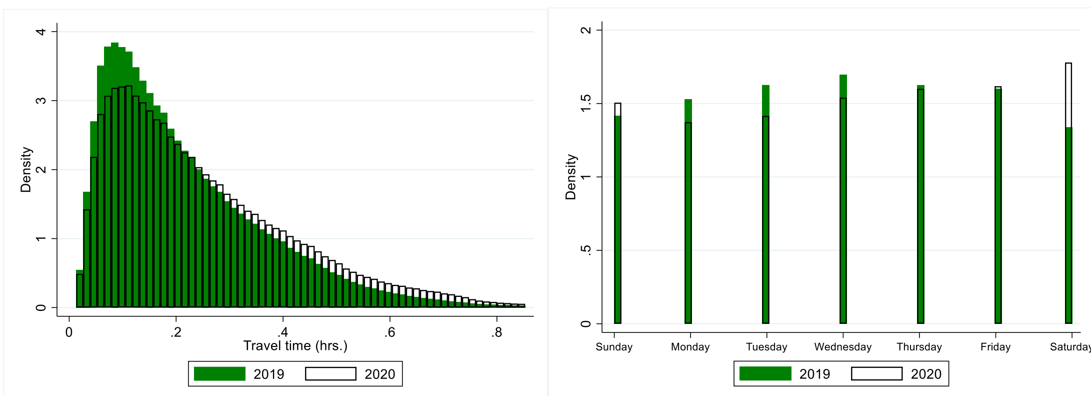
---

[19] The first time Montreal imposed a curfew measure during the Covid-19 pandemic was on January 9, 2021. For more details, see <https://globalnews.ca/news/7558944/quebec-curfew-coronavirus-lockdown-measures/>.

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



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

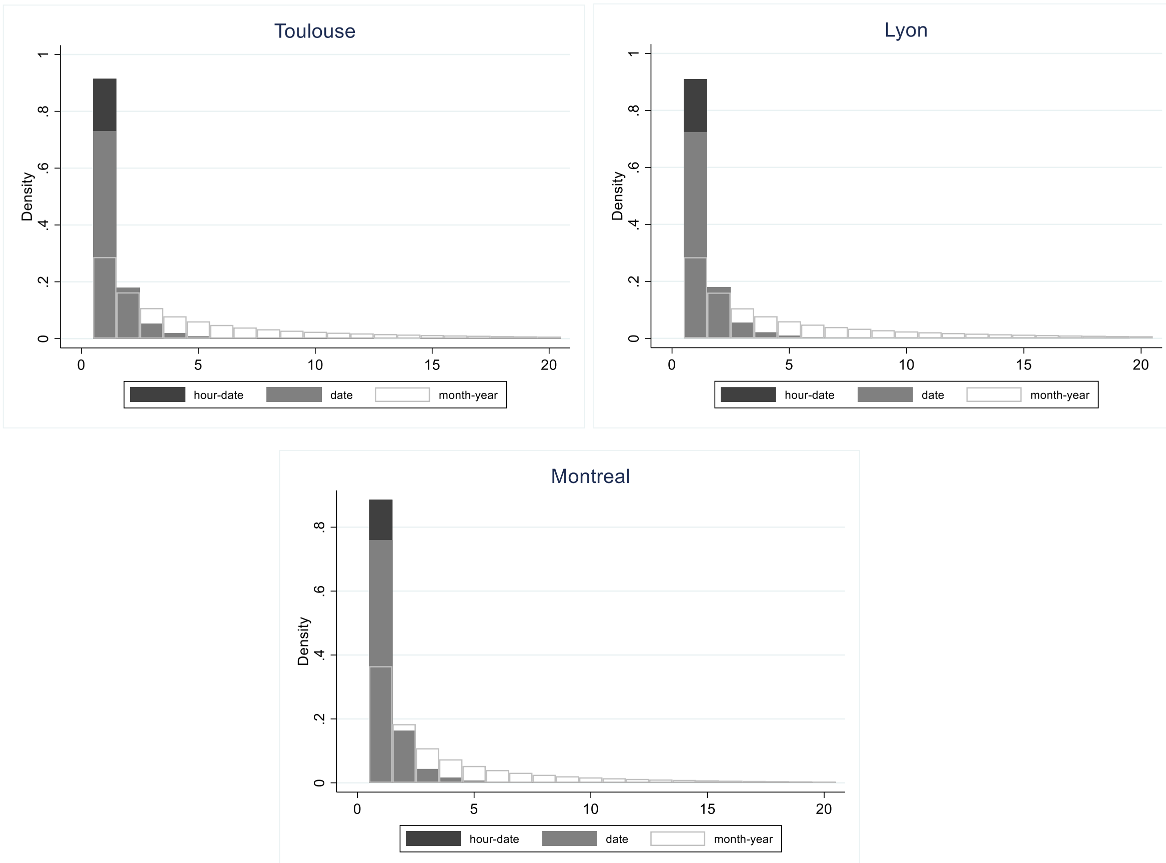


Regarding travel time graphs, for the 3 cities, a rightward movement in the distribution is observed, being more likely to see longer travel times in 2020 compared to 2019. This is expected, as it is in line with higher travel distances previously seen.

Likewise, in the case of Toulouse and Lyon, there are no significant variation in the daily distribution of BSS trips between 2020 and 2019. However, for Montreal a relevant change is visually observed, with more trips on weekends and less on weekdays, which could be consistent with teleworking policies.

Finally, the Graph 10 shows the distribution of O&D BSS trips, considering different time windows (i.e., hourly, daily, and monthly trips, respectively).

Graph 9: Density histogram of O&D trips using the BSS, for Toulouse, Lyon, and Montreal



First, we can observe that, as we increase the time window of O&D trip variable, its variance increases as well (e.g., in Toulouse case, if we consider the hour-day time window, more than 90% of the observations only present 1 trip). This is important, because it presents a trade-off for an econometric analysis that considers O&D trips as a dependent variable: if we consider O&D trips at the hour-day level (high disaggregation): [i] our dependent variable will have a smaller variance, which is undesirable since it is necessary for an econometric analysis, however [ii] it also maximizes the variability of the explanatory variables, which is desirable since it allows us to better identify the effect of each regressors. In the opposite case (i.e., monthly O&D trips), the trade-off goes in the opposite direction (larger variance of the dependent variable, but lower variability of the regressors due to the aggregation).

The level of data aggregation is an important issue, which will be developed in more detail in the next section, where we present the econometric model and the methodology.

3 Econometric methodology

3.1 Specification

Considering that the number of trips using BSS is a counting variable, it can be described as a Poisson distribution[20-21], where the average number of trips ($\lambda_{od,t}$) between each origin (o) and destination (d) every period (t), is expressed as the exponential of a linear combination of independent regressors that can be grouped under three sets: [i] O&D[22] specific variables (X_{od}); [ii] origin specific (X_o) and destination specific (X_d) variables; and [iii] non-O&D specific variables (X_t).

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

Additionally, to describe the Covid-19 effect/change on each of these variables, the parameters to be estimated have the following expression:

$$\alpha_i = \alpha_{oi} + \alpha_{1i}D\ ;\ \ i \in \{od, o, d, t\}$$

Where:

$$D = \begin{cases} 0, & if\ t\ belongs\ to\ the\ period\ \boldsymbol{before}\ 1^{st}\ confinement\ in\ France \\ 1, & otherwise \end{cases}$$

In this regard, α_{oi} represents the partial effect for each of the variables before the first confinement/lockdown in France, whereas $\alpha_{oi} + \alpha_{1i}$ is the effect post-first lockdown period. Therefore, our attention will be on α_{1i}, which represents the change or difference between both periods, being our proxy to the Covid-19 effect on these variables. Also, and even though the first lockdown in France lasts from March 17 to May 10 in 2020[23], for simplicity we have assumed that it lasts 3 months, between March and May 2020[24]. Thus, the pre-first confinement period consists of 2019 and January-February 2020, while the post-first confinement period considers June to December 2020. Finally, because the Montreal's BSS data is from April to November each year, the Covid-19 effect (α_{1i}) is only the comparison between 2020 and 2019.

---

[20] For more details, see Greene (2017).

[21] 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.

[22] O&D means an origin and destination trip between 2 specific bike stations, directionally.

[23] May 11, 2020 is known as the "first stage opening" (Ivaldi & Palikot, 2020).

[24] We assume this because the complete deconfinement was carried out in several stages, ending by the end of May 2020.

3.2 Variable selection

Based on the model presented, we now specifies the variables 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_n).

First, related to the dependent variable for the econometric estimation, we mainly opt for the maximum level of disaggregation: we use number of O&D trips at hour-day level. As explained in the previous section, although using this level of disaggregation makes the variance of O&D trips smaller, this maximizes the variability and explanatory power of our model, by taking advantage of that many variables are at hour-day level, such as weather regressors (Rain, Temperature, Wind speed and Solar radiation) and public transport variables (Bus, Metro and Tram users for the case of Lyon). This is important, since the main objective of this paper is to predict what happens to the number of BSS trips in certain scenarios (e.g., more rain, longer distances, or travel times, etc.).

Then, for the O&D specific variables (X_{od}) we considered two variables: Travel distance (in km.) and Travel time (in hours). Related to the Travel distance variable, we expect a negative effect, since longer trips should discourage the use of the BSS. 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 absence of bicycle stations very close by or because people could make trips walking.

Related to the non-O&D specific variables (X_t), we used: weather variables (Rain, Temperature, Wind speed and Solar radiation) and public transport variables (Bus, Metro and Tram users, respectively), in addition to the variables: day of the week (Monday, Tuesday, etc.), type of day (Public holiday, School vacations, Ordinary and Summer) and fixed effect by month. In this sense, we expect on average a negative effect of variables Rain, Wind speed and Solar radiation on the BSS use, since they are associated with unfavorable weather conditions, or situations that may affect health. Meanwhile, we expect a positive effect of Temperature on the bicycles use, since people should not use them in very cold situations. Likewise, we expect a negative effect of public transportation variables on the BSS use, due to the substitution between these transportation modes.

Finally, considering the origin specific (X_o) and destination specific (X_d) variables, we used information from the French census and the BPE. In this case and knowing the IRIS area associated to each BSS station, we matched some demographic and services variables to each of them. Thus, for each O&D trip observation in our database we have 2 variables for each demographic and service variable, which are related to the area of origin and destination of each trip, respectively.

Regarding the demographic data (2017 French census), we pay attention to those variables that could be related to the probability of getting Covid-19, and those that, in case of having caught the virus, could increase its dangerousness (risk factors). Then, we focused on the following variables[25], which are calculated at the origin and destination area of the BSS trip, respectively: Number of living people; Average age of people; Student proportion; Foreigners proportion; Women proportion; Mode of the highest education level of people; Mode of the number of people living in the household; Mode of the household family structure; Mode of the most used transportation mode to work; Mode of the number of vehicles in the household; Mode of the type of activity performed by the person; and Mode of the person's socio-professional category.

Likewise, for services data (2019 BPE) we pay attention to those variables that were related to people's daily activities, as well as those related to recreational issues. Thus, we chose next variables, which are calculated at the origin and destination area of the BSS trip, respectively: 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[26] ("chauffeur driven vehicles"); Number of outdoor playgrounds and play areas; and Number of cinemas.

Finally, considering that we had less information for Montreal, the model is much simpler. First, the dependent variable is again the O&D trips at hour-day level ($\lambda_{od,t}$) and the independent linear variables are Travel distance (in km.), Travel time (in hours), day of the week (Monday, Tuesday, ...) and fixed effects per month.

[25] As the information from the French census is at the individual level, we had to aggregate it in some way to obtain information at the IRIS area. Thus, depending on the type of variables, we calculated the sum, average or mode of the variables by area. The sum and average were calculated for numerical variables. The mode was calculated for categorical variables. Likewise, some categorical variables can take many different values. Thus, for a detailed explanation of each of these variables, please revise the Appendix B.

[26] 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 for them in advance. Services are personalized and a fixed price is decided in advance.

3.3 Estimation procedure

Considering that the Poisson model is a nonlinear model, we use Maximum Likelihood Estimation to estimate the parameters. All estimations are performed using the robust standard error option due to heteroscedasticity potential problems (White, 1980). In addition, it is worth noting that we are working with population data (not a sample of it), which helps us to obtain a good estimate of the regressors effect. Finally, despite we do not have a variable that shows the availability of bicycles in each station and moment of time, the hourly variability of our database helps us to have results without potential restraints in this sense.

To check the robustness of our results, we perform different exercises for Toulouse and Lyon in the next section. The first analysis consists of estimating our Poisson model for 4 different periods/cohorts of comparison. The first regression performs the estimation as explained in Section 3.1 (pre-first confinement period from January-2019 to Febrary-2020, and post-first lockdown period from June-2020 to December-2020). The second regression only performs the comparison between 2020 and 2019, considering June to December. The third regression makes the comparison between 2020 and 2019, period June-October. Finally, the fourth regression compares 2020 and 2019, during the period November-December exclusively.

In this regard, the second regression estimation aims to compare 2020 and 2019 considering the same months (June to December) to avoid seasonal effects. The third and fourth regressions seek to separate the regression between, the period without relevant Covid-19 measures and low Covid-19 cases in France (June-October), and the second lockdown period in France (November-December), which started October 30, 2020[27]. With this methodology it is possible to dynamically observe how robust the results are, being the June-October period probably the most likely to be projected into the future, given its character of "pseudo-normality" after the first confinement in France. Also, this exercise indirectly allows us to control for the level of Covid-19 cases over time.

The second robustness exercise is the estimation of the model but only showing the Covid-19 effect/change (α_{1i}) on Travel distance variable considering different time windows (every 2 hours). This analysis is valuable because it allowed us to take advantage of trip variability during the day, which is large. It also showed us which the most important time slots/windows are, in order to get an idea of the user's profile or the reason why they use the bicycles (work, leisure, etc.).

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

The last relevant exercise is related to the possibility of ranking the different results, since our model has several regressors. To rank these effects, we regressed our model but now standardizing/normalizing its continuous regressors[28], which implies that now each estimated effect is with respect to the variation of 1 standard deviation of these continuous variables. This is useful because it allowed us to rank, according to their relevance[29], the 12 continuous (standardized) variables and 12 categorical/dummy variables[30], both for the Covid-19 effect (α_{1i}) and the complete post-first confinement effect $(\alpha_{oi} + \alpha_{1i})$ respectively, in the cities of Toulouse and Lyon.

Finally, considering the particular situation for Montreal, we make an ad-hoc analysis. First, we perform the same period/cohort regressions. The first regression compares 2020 and 2019, April-November period, controlling for Travel distance variable, Travel time variable, the day of the week (Monday, Tuesday, etc.) and the fixed effects by month, as well as their multiplications with the dichotomous variable D to obtain the Covid-19 effect (α_{1i}) (this is our Poisson model for Montreal). The regressions second and third are the previous regression separated between the periods April-August (second regression) and September-November (third regression). As in the previous cases, these period/cohort regressions seek to show the robustness of the observed results. Finally, and similar to the Toulouse and Lyon cases, we performed the estimation but showing only the Covid-19 effect (α_{1i}) on Travel distance variable for different time windows (every 2 hours), to see how the Covid-19 effect changes throughout the day.

The following section shows the econometric results for the cities of Toulouse and Lyon in France, and Montreal in Canada.

---

[28] To standardize the 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.

[29] 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 for the Toulouse (Table 6 and 7) and Lyon (Table 12 and 13) results.

[30] For the case of the 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.

4 Econometric results

4.1 Results for Toulouse

4.1.1 Effects of O&D specific variables

Following the methodology explained in Section 3.3, below are the regression results considering different periods/cohorts but only showing the O&D specific variables, i.e., Travel distance and Travel time, as well as their multiplication with the dichotomous variable D, to see the Covid-19 effect (α_{1i}) on these variables.

Table 4.a: Poisson regression for Toulouse. Effects of O&D variables[31]

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 in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results corroborate our initial predictions. Regarding the Travel distance variable, its partial effect is negative during pre-first lockdown period, as an increase of 1 kilometer in travel distance decreases the average number of trips per hour by 1% approximately. However, the Covid-19 effect is positive in all these regressions. The results show that post-first confinement more trips were made per additional kilometer, indicating that people would be willing to travel longer distances post Covid-19 outbreak, even during the pseudo-normal period (June-October), probably to avoid social interaction. It is worth mentioning that these results are statistically significant at 99% confidence.

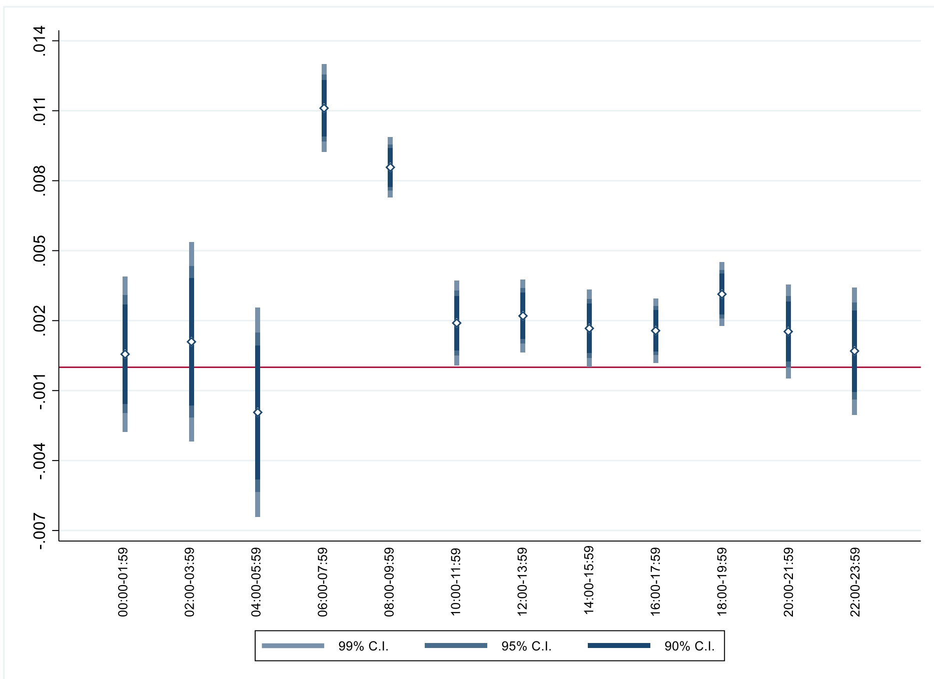
In relation to the Travel time variable, we also see interesting results. The partial effect in all period regressions is positive during pre-first confinement period, which is an expected result. However, the change effect (Covid-19 effect) is positive in all period regressions (except in the fourth regression, which is statistically non-significant at

[31] The variables that are left side fitted in the Table 1 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 the variables is maintained in all the regressions shown hereafter.

95% confidence), which would indicate that the population is currently more willing to spend more time cycling, possibly avoiding faster alternatives such as public transport.

Next, the Graph 10 shows the Covid-19 effect (α_{1i}) on Travel distance variable, and its confidence intervals at 99%, 95% and 90%, considering different time windows during the day (every 2 hours).

Graph 10: Covid-19 effect on travel distance variable every 2 hours for Toulouse



The results show that the main time blocks that explain the change in Travel distance are related to the departure hours to work, especially between 06:00 and 10:00 hours. These results are interesting, as they suggest that this change would be mainly explained by people that use the BSS for travelling to work or similar activities in Toulouse (like going to school).

4.1.2 Effects of non-O&D specific variables

Now we present the same periods/cohort regressions as above, but only showing the non-O&D specific variables, such as the variables day of the week (Monday, Tuesday, ...), type of day (Public holiday, School vacations, Ordinary and Summer), public transport (Bus, Metro and Tram users), the outside option and weather regressors (Rain, Temperature, Wind speed and Solar radiation).

The Table 4.b only shows the results of the variables day of the week and type of day.

Table 4.b: Poisson regression for Toulouse. Effects of non-O&D variables

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

In relation to the day of week variable, the base group is "Sunday". It shows that, during pre-first confinement, the other days present comparatively fewer trips compared to the base group (*ceteris paribus*). Moreover, in all regression (except the third one) the Covid-19 effect is negative (with at least 95% of statistical confidence), which is consistent with people using the BSS less due to teleworking. Notwithstanding, it is important to note that the Covid-19 change is statistically non-significant in the third regression, which would indicate that during pseudo-normal period (June-October 2020) the population returned to use the BSS as during pre-first confinement, being evidence of BSS resilience.

On the other hand, the type of day variable shows notable results. The base group is "Ordinary day". The Covid-19 effect shows a positive increase in trips during Summer, which is consistent across all regressions and with the idea that there was a recovery of BSS trips during the pseudo-normal period. The Ordinary day category, instead, shows almost no statistically significant changes, which would be consistent with the idea that people post-first confinement kept their BSS use relatively stable as before pandemic. Finally, the Covid-19 effect on School vacations was omitted due to perfect collinearity.

The Table 4.c below presents the regression outputs of the non-O&D variables related to public transport system (Bus, Metro and Tram users), weather conditions and outside option.

Table 4.c: Poisson regression for Toulouse. Effects of public transport system and weather conditions

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 in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Regarding the public transport variables, we can see a negative effect during pre-first confinement period (in all public transport systems and all period regressions), which is expected considering the substitution between the public transport system and the BSS. However, in almost none of the presented period regressions is observed a statistically significant change effect (Covid-19 effect), which would indicate that the level of substitution remained relatively constant after Covid-19 outbreak in Toulouse. Only a negative Covid-19 effect is observed in Tram variable, first and second regressions, which would indicate that substitution with the BSS system slightly increased.

On the other hand, the weather variables show interesting results. Regarding the Rain regressor, the pre-first confinement effect is negative, which is an expected result. However, the Covid-19 effect is positive, which is robust to the different period regressions except for third one (statistically non-significant), probably because it coincides with the summer period. In our opinion, these results show an increased willingness to use the BSS even in more adverse weather conditions, probably to avoid more congested modes of transportation.

The Temperature and Solar radiation variables also present results to be highlighted. The Temperature variable has a positive effect pre-first confinement, which increases post-first confinement (positive Covid-19 effect), being statistically significant in all period regressions. This behavior makes sense, given that lower temperatures should discourage the use of the BSS, and its higher sensitivity to it (positive Covid-19 effect) is probably explained by people's increased aversion to getting sick after the start of the pandemic. The Solar radiation variable shows the same expected behavior, since the higher the solar radiation, the lower the number of BSS trips is expected to be. What is striking is that this effect increases post-first confinement, which could be explained in a similar way to what happened with 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

Finally, the Tables 4.e and 4.d summarize the main 12 continuous (standardized[32]) and 12 categorical/dummy effects[33] for Toulouse, both for the Covid-19 effect (Table 4.d) and for the complete post-first confinement effect (Table 4.e), respectively. All these effects are statistically significant at least at 95% confidence.

[32] 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.

[33] For the case of the 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.

Table 4.d: Main Covid-19 effects (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 4.e: 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

Regarding the Covid-19 effect on categorical/dummy regressors (Table 4.d), the variable day of the week (Monday, Tuesday, etc.) stands out, which makes sense since an important part of the mobility changes were due to Covid-19 measures, such as the teleworking. On the other hand, the results indicate that in those areas where most households are composed of 1 or 2 people have experienced an increase in origin and destination trip after the first confinement in France. This may be because the population, after Covid-19, preferred to travel to areas with fewer residents per household as a way to decrease the contagion probability. Finally, we see a decrease in trips to those areas where most of the families are “woman with children”. In our opinion, a possible explanation for this could be linked to discrimination against them in the labor market, affecting their employability due to childcare.

Considering now the Covid-19 effect on continuous (standardized) variables (Table 4.d), Travel distance highlights, showing that the increased willingness to make longer trips is one of the main changes from Covid-19 outbreak. This result is probably explained by the change in people's habits in favor of BSS, as a way to decrease the probability of getting Covid-19. The Temperature variable also stands out among the most important changes, which shows that the population would be less likely to travel in the presence of lower temperatures, probably to avoid exposure to situations that could affect their health since the beginning of the pandemic.

The Average age change is another important output. The results indicate a positive Covid-19 change to those areas where people are older. A possible explanation of it could be that, given that age is a risk factor for Covid-19, both older people living in those areas and visitors opted for transport modes with a lower risk of contagion (like the BSS).

Finally, and with respect to the complete post-first lockdown effects (Table 4.e), the main variables that explain the use of BSS are those related to public transport, i.e., Bus, Metro and Tram users, as well as the outside option variable. In our opinion, these results would indicate that the BSS use is explained more by commuting than by leisure trips. In addition, Travel distance and Temperature stand out as important regressors. Lastly, the Proportion of students is an important variable in explaining travelling to and from certain areas.

4.2 Results for Lyon

4.2.1 Effects of O&D specific variables

Following the same period/cohorts regressions and econometric model presented for Toulouse, the Table 4.f presents the Lyon results only showing the O&D specific variables, i.e., the Travel distance and Travel time variables, and their Covid-19 effects (α_{1i})

Table 4.f: Poisson regression for Lyon. Effects of O&D variables

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

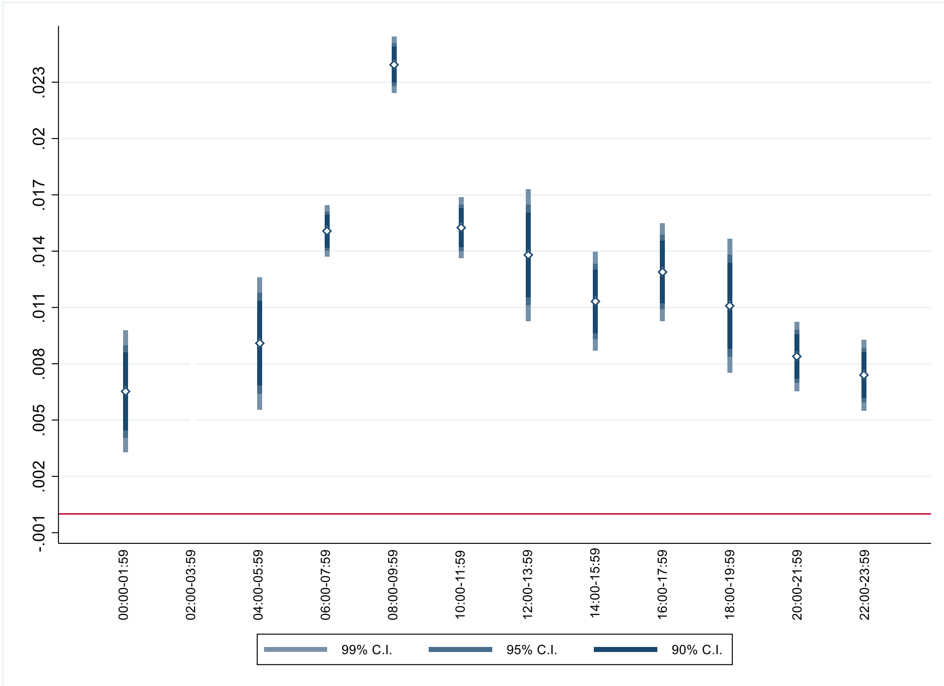
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Like the results presented for Toulouse, the Lyon findings are consistent with our predictions. Regarding the Travel distance variable, the pre-first confinement effect is negative in all regressions, indicating that one additional kilometer implies a reduction of 2%-3% trips per hour on average. However, and like Toulouse case, the Covid-19 effect is positive and statistically significant at 99% confidence in all cohort regressions, indicating that more trips per additional kilometer were made post-first lockdown than before it.

On the other hand, the Travel time variable shows different results for Lyon than those observed for Toulouse. The change effect (Covid-19 effect) is statistically non-significant. In other words, there was not a greater willingness to make longer duration trips in Lyon after Covid-19 outbreak, *ceteris paribus*.

Now, like Toulouse case, the Graph 11 presents the Covid-19 effect (α_{1i}) on Travel distance variable, and its confidence intervals at 99%, 95% and 90%, considering different time windows during the day (every 2 hours), for the city of Lyon.

Graph 11 Covid-19 effect on travel distance variable every 2 hours for Lyon



The results for Lyon show that, like Toulouse case, the main time block that explain the increase on the Travel distance variable is between 08:00 and 10:00 hours. These results again reinforce the idea that the change on this variable would be linked to people using the BSS to travel to their jobs or related activities (e.g., going to college).

4.2.2 Effects of non-O&D specific variables

The Table 4.g and 4.h present the same period/cohort regressions but only showing the non-O&D specific variables day of the week (Monday, Tuesday, ...), type of day (Public holiday, Vacations, Ordinary and Summer), public transport (Bus, Metro and Tram users), the outside option, and the weather conditions (Rain, Temperature, Wind speed and Solar radiation). The Table 4.g presents the results just showing the variables day of the week and type of day for Lyon.

Table 4.g: Poisson regression for Lyon. Effects of non-O&D variables

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 in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Once again, the variable day of week has as its base group “Sunday”. The results show that, for the period pre-first confinement, all the other days present fewer trips compared to “Sunday”. Notwithstanding, and in contrast to what was observed in Toulouse case, the Covid-19 changes are statistically non-significant in all period regression, except for the third column (third regression), where it is positive on all days and statistically significant at 99% of confidence. These results are quite interesting as, in a situation of pseudo-normality (June-October period), the population probably will use the BSS even more than pre pandemic, which provides evidence of resilience and a permanent positive change in the use of BSS.

Regarding the type of day variable, the base group is again “Ordinary day”. The results are like those observed for Toulouse. First, we see a positive Covid-19 effect on the Summer, like Toulouse case. Second, the Covid-19 change on Public holiday is negative in all period regressions, with exception in the third column (third regression). Third, the Covid-19 effect on the Ordinary day is statistically non-significant in almost all regressions, like Toulouse case. From our point view, this evidence is consistent with the increase in the BSS use in Lyon, at least during pseudo-normality period. Finally, again the Covid-19 effect on School vacations was omitted due to perfect collinearity.

Next, the Table 4.h shows the results of the non-O&D specific variables for public transport, weather conditions, and outside option.

Table 4.h: Poisson regression for Lyon. Effects of public transport system and weather conditions

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 in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In relation with the public transport variables, we see noticeable results. First, we observe a negative effect during pre-first lockdown period (in all transport systems and all period regressions) as we saw in for Toulouse, which is expected given the substitutability between the different transport modes. Notwithstanding, and in contrast to what was observed for the Toulouse case, we see a positive Covid-19 effect in all public transport systems and in almost all regressions (except fourth one). This suggests that, since Covid-19 outbreak, the public transport (Bus, Metro and Tram) in Lyon is less substitute for people that use the BSS, which would make sense given the population's aversion to using congested transport systems, as a way of reducing the contagion probability.

The weather variables have some similar results with Toulouse. Regarding the Rain variable, the Covid-19 effect is statistically non-significant, except in the second regression, where it is positive at 90% of statistical confidence. On the other hand, the Covid-19 effect on Temperature is in line with what was observed for Toulouse, with a positive and statistically significant change in almost all regressions (except the fourth regression). It would be consistent with a lower willingness to use the BSS in the presence of lower temperatures after the Covid-19 outbreak, probably to avoid exposure to situations that may affect health.

The Solar radiation variable present results like those observed in Toulouse, with a negative Covid-19 change in all regressions, which would be consistent with people avoiding high-risk health situations after Covid-19 outbreak. Finally, the Covid-19 effect on the Wind speed is mixed, showing a positive effect in the first regression (Base model), but a negative effect in the third regression (pseudo-normal period).

4.2.3 Standardized results

Lastly, the Table 4.i and 4.j present the main 12 continuous (standardized[34]) and 12 categorical/dummy[35] variables for Lyon, both for the Covid-19 effect and for the complete post-first confinement effect, respectively. All these effects are statistically significant at least at 95% confidence.

Table 4.i: 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

[34] 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.
[35] For the case of the 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.

Table 4.j: 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 continuous (standardized) variables (Table 4.i), the public transport regressors stand out. Indeed, the variables Bus, Metro a Tram users present a positive Covid-19 effect, which implies a decrease in substitutability with the BSS in Lyon. In addition, like in Toulouse case, the variables Travel distance and Temperature once again are relevant, showing a greater willingness to take longer trips and a lower propensity to travel in the presence of low temperatures the Covid-19 outbreak. In the same line, the Average age variable is relevant once again, having a positive Covid-19 effect for origin trip. This finding is interesting since older people are probably using more bikes than before pandemic, as a way to reduce the contagion risk and by the fact that age is a risk factor related to Covid-19.

Another interesting result is related to the "Women proportion" variable. The result states that after Covid-19 outbreak fewer trips are observed from those areas where there are proportionally more women. One explanation could be related to risk aversion: if it is assumed that women are more risk averse than men (e.g., women are more fearful than men of catching the virus), it is possible that women decided to stay at home more than men after Covid-19 outbreak. Another possible explanation could be related to discriminatory issues towards women, such as in the labor market, which leave them more at home as a consequence of the health crisis.

On the other hand, the main Covid-19 effects about categorical/dummy variables are related to demographic variables (Table 4.i). First, the variable "Woman with children" stands out. This variable indicates that, since Covid-19 outbreak, there has been a significant reduction in the number of trips to areas where most of the families are women and children only. Once again, this variable may be indicating some type of employment bias or discrimination against women, product of job precariousness or for family reasons (childcare).

The other categorical variables that show Covid-19 effects are mostly associated with household family structure (e.g., areas where mostly only men or only women live, couples with or without children, etc.). In our opinion, these variables 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 variable "families without cars" stands out. Indeed, in those areas where the majority are families without cars, there is an increase in the BSS use since Covid-19 outbreak. This is interesting because it would show a greater willingness to use BSS possibly to the detriment of public transport.

Finally, regarding the post-first confinement effects (Table 4.j), there are some interesting results. As in Toulouse case, in Lyon the main variables that explain the use of BSS are related to public transport, which show the degree of substitution between these transport modes and that the BSS would be used more for commuting than for leisure purposes. Likewise, the Travel distance and Temperature variables again stand out as in the case of Toulouse.

4.3 Results for Montreal

The interpretation of the Montreal results is simpler than for Toulouse and Lyon since we have fewer variables. Also, considering that for Montreal we only have information between April and November in both years, the Covid-19 effect is essentially a comparison between 2020 and 2019. Table 4.k below shows the period/cohort regressions for Montreal.

Table 4.k: Poisson regression for Montreal

VARIABLES	(1) Base Model	(2) Comparison April to August	(3) Comparison September to November
Travel distance	-0.0378034***	-0.0385391***	-0.0343202***
(Travel distance)*D	0.0180144***	0.0173538***	0.0185434***
Travel time	0.4909115***	0.5104777***	0.4131787***
(Travel time)*D	-0.1824820***	-0.1843403***	-0.1608801***
Monday	-0.1018922***	-0.1081461***	-0.0836320***
Tuesday	-0.1187613***	-0.1293736***	-0.0884616***
Wednesday	-0.1180743***	-0.1291170***	-0.0868516***
Thursday	-0.1166795***	-0.1262960***	-0.0883400***
Friday	-0.0996530***	-0.1112741***	-0.0668750***
Saturday	-0.0251872***	-0.0265409***	-0.0219098***
(Sunday)*D	-0.0666852***	-0.0707169***	-0.0537372***
(Monday)*D	-0.0448921***	-0.0469911***	-0.0398974***
(Tuesday)*D	-0.0383364***	-0.0318847***	-0.0560466***
(Wednesday)*D	-0.0294039***	-0.0186409***	-0.0570222***
(Thursday)*D	-0.0374008***	-0.0321160***	-0.0524376***
(Friday)*D	-0.0398615***	-0.0326256***	-0.0591094***
(Saturday)*D	-0.0372120***	-0.0386363***	-0.0295885***
Constant	0.1994433***	0.2037932***	0.1919781***
Observations	7,320,207	5,180,760	2,139,447
Pseudo R-squared	0.00348	0.00384	0.00203
Month FE	YES	YES	YES

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

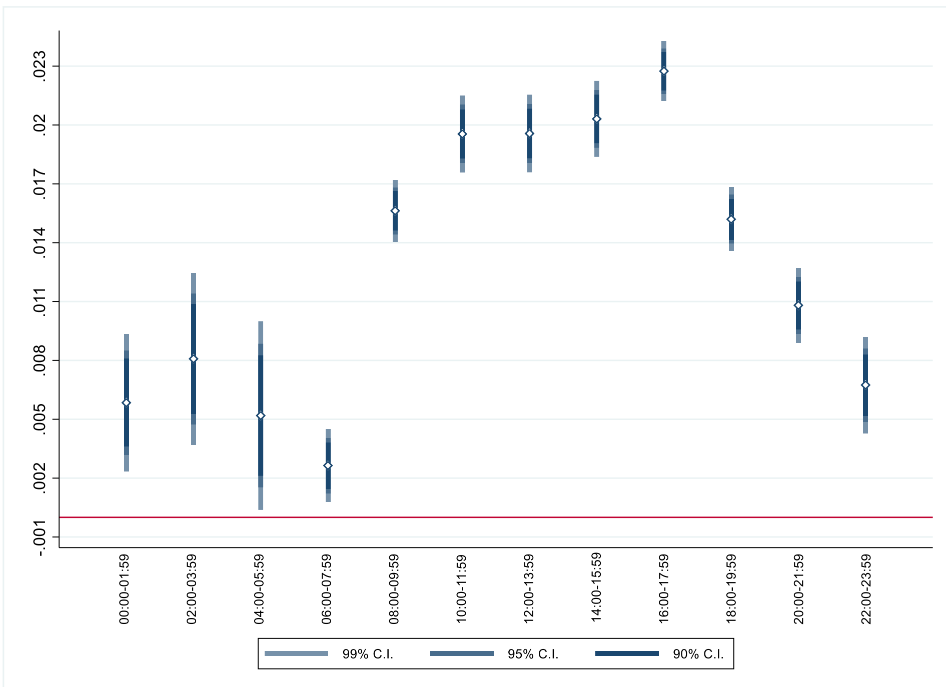
The Montreal results, like those already shown for Toulouse and Lyon, again corroborate part of our previous findings. Regarding the Travel distance variable, we again observe for 2019 a negative effect, implying that each additional kilometer represents a 3-4% decrease in average hourly trips. Similarly, and consistent with what was observed for Toulouse and Lyon, the Covid-19 effects are positive, which reaffirms our assertion that people are less sensitive to distance after the Covid-19 outbreak, possibly to avoid public transportation. It is worth mentioning that these results are consistent for all period/cohort regressions and with a statistical significance level of over 99% confidence.

Notwithstanding, the Travel time variable presents different results. For the case of Montreal, contrary to what was observed in Toulouse (positive result) and Lyon (statistically non-significant evidence), the Covid-19 effect is negative, which would be indicative that people were less likely to make longer duration trips during 2020 using BSS, *ceteris paribus*.

The day of the week variable shows interesting results. In this case, the Covid-19 effect is negative on all days and in all period regressions, which goes in the opposite direction to what was evidenced especially in Lyon, i.e., there is a no significant recovery of trips in the pseudo-normal period. One explanation for this could be that telework policies were more effective in Montreal, evidencing a generalized drop in BSS use during 2020.

The Graph 12 shows the Covid-19 effect (α_{1i}) on Travel distance variable, and its confidence intervals at 99%, 95% and 90%, considering different time windows during the day (every 2 hours).

Graph 12: Covid-19 effect on travel distance variable every 2 hours for Montreal



In this case, and in contrast to the case of Toulouse and Lyon, Montreal shows that the greater propensity to make longer BSS trips after Covid-19 outbreak is homogeneously distributed in the time slots between 10:00 and 18:00 hours. Although these results are not directly associated to peak hours, it is worth to remember that, as shown in Section 3, Montreal shows a different behavior on its trip start hour distribution in 2020 compared to Toulouse and Lyon, probably due to people propensity to avoid traveling during peak hours, and the lack of curfew measures in Montreal during 2020.

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 the BSS. For the 3 cities (Toulouse, Lyon, and Montreal), a clear increase is observed in travel distance after Covid-19 outbreak, which is statistically significant at 99% confidence and robust to different period regressions. These findings have been consistent across all our exercises and are likely to be permanent.

Then, the time-slot analysis (every 2 hours) of the Covid-19 effect on the Travel distance variable showed, at least clearly for Toulouse and Lyon, that the main block hours which explain the increase in travel distance are those related to peak hours, especially associated with the beginning of the working day. This evidence allows us to affirm that the change in travel distance would be explained mainly by people who decided to use the BSS to go to work or similar activities (such as going to university).

On the other hand, the periods/cohorts analysis showed a mixed recovery in the BSS use after the first confinement, especially in the June-October period (pseudo-normal period). Indeed, in Toulouse Case, during the pseudo-normal period, there is no statistically significant difference between the trips before and after the first confinement period in France, which shows a recovery to pre-pandemic levels. In the case of Lyon, instead, it shows that in the June-October comparison there was an increase in trips with respect to the pre-first confinement period, which is statistically significant at 95% confidence. In our opinion, these results would show the resilience of the BSS in these cities, especially in Lyon where an increase in trips is seen. For the case of Montreal, instead, we see a decrease in the number of trips using BSS during 2020 compared to 2019.

The weather variables also present salient results. In the case of Toulouse, after the Covid-19 start there is a general 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 change on Wind speed and a lower sensitivity of Rain only in the period June-December. Likewise, a greater sensitivity to the Temperature variable is observed for both cities. This evidence would indicate a greater willingness to use BSS even in more adverse climatic situations (more rain and wind), probably as a consequence of avoiding the public transport use.

Finally, although not all the results coincide between Toulouse and Lyon, the standardized regressions provide interesting findings for both cities. First, the variable "Average age" shows a positive change post-first confinement in both cities. This is expected given that age is a risk factor for Covid-19, so visitors and older people prefer to use a transport mode with lower risk of contagion, such as the BSS.

In the same line, the changes in the Travel distance and Temperature variables in Toulouse and Lyon stand out. In our opinion, this evidence shows an important change in the habits of the population after the Covid-19 start, as people would be willing to travel longer distances and avoid traveling in low temperatures in order not to expose their health.

Another variable that is remarkable in Toulouse and Lyon is "Woman with children". Indeed, the evidence shows that there is a decrease in trip in those areas where women with children are the majority. In this regard, a possible reason for this could be some discrimination in the labor market against them, which ends up affecting their employability due to childcare.

Similarly, especially in Lyon, the variable "Women proportion in each area" highlights. The evidence shows that, after the first lockdown in France, fewer BSS trips were made from those areas where more women live. The reasons may be various, but in principle we have 2 hypotheses: (i) women are probably more afraid of getting the virus than men (they are more risk averse); or (ii) there is some discrimination in the labor market that made them end up staying at home more than men.

Finally, it is important to highlight that the main variables that explain the post-first confinement effect $(\alpha_{oi} + \alpha_{1i})$ in both cities are related to public transport (Bus, Metro and Tram users), which show the substitution effect with the BSS. From our point of view, this evidence reinforces the idea that BSS trips are mainly motivated by work transport purposes, rather than for leisure trips.

The conclusions of the present work provide relevant information about changes of BSS-users behavior, which have the potential to be permanent. These inputs are valuable, since it is possible to make an accurate analysis of what happened to evaluate different public policies in this system. In this sense, it is important to remember the difficulty of changing the habits of users (due to switching cost) and that the population has already made some changes in favor of cycling (it is already a sunk cost), so any public policy in this system starts with an advantage. Thus, the main message is that today we have a unique opportunity to make investments in this system, seeking to materialize the positive changes observed and thus promote the use of bicycles permanently.

In this regard, some public policies that could be implemented are related to adding technology to the BSS in both cities. Indeed, given that people would be traveling longer distances and for longer periods of time, and mainly motivated by those who use the BSS for travelling to work, it would be desirable to have a timer to better control travel time and thus optimize the restriction of free minutes per trip[36].

Likewise, it would be desirable to have lighter bicycles, as well as electric version (specifically for Toulouse), to promote its use by people who, although considering the BSS as an alternative, may not be using it due to a physical disability or for other reasons (faster travel, difficulties on the ground, among others). 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 that we have in France is the BSS "Vélib'-Metropole" in Paris. The bikes are lighter there, have timer and electric versions, which are surely designed for a larger city that on average has longer trips. Thus, the changes observed in bicycle use after the Covid-19 outbreak are good reasons to seriously evaluate the investment in technology in the BSSs of Toulouse and Lyon.

Finally, extensions of this paper are related to make the functional form of our model more flexible, to see non-linear effects of certain variables (e.g., Travel distance variable o Travel time variable). Also, it could be valuable to have additional data, such as the average wage per area, to see the differences in the Covid-19 effects considering the socioeconomic status of people.

[36] At the Toulouse (VélÔToulouse) and Lyon (Vélo'V) BBSs, the annual plans consider a free minutes 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>

References

Bührmann, S. (2007). New Seamless Mobility Services: Public Bicycles Policy Notes (NICHES Policy Note 4). Rupprecht Consult Forschung & Beratung GmbH.

Chai, X., Guo, X., Xiao, J., & Jiang, J. (2020). Analysis of Spatial-temporal Behavior Pattern of the Share Bike Usage during. arXiv: Physics and Society.

Eren, E., & Uz, V. E. (2020). A review on bike-sharing: The factors affecting bike-sharing demand. Sustainable Cities and Society.

Fishman, E. (2020). Bike Share. Routledge.

Greene, W. (2017). Econometric Analysis. Pearson, 8th Edition.

Ivaldi, M., & Palikot, E. (2020). Sharing when stranger equals danger: Ridesharing during Covid-19 pandemic. Covid Economics, pp. 68–93.

Li, A., Zhao, P., He, H., & Axhausen, K. W. (2020). Understanding the variations of micro-mobility behavior before and during COVID-19 pandemic period. Proceedings of TRB 2021, IVT ETH Zurich.

Luc, N. (2008). Vélib one year later. Sustainable Transport, Number 20.

Moro, S., Imhof, A., Fettermann, D., & Cauchick-Miguel, P. (2018). Barriers to bicycle sharing systems implementation: analysis of two unsuccessful PSS. Procedia CIRP, 191-196.

Ricci, M. (2015). Bike sharing: A review of evidence on impacts and processes of implementation and operation. Research in Transportation Business & Management, 28-38.

Rocci, A. (2015). How Breaking Habits? Accompanying Programs for Travel Behaviour Change. Espace populations sociétés.

Shaheen, S., Guzman, S., & Zhang, H. (2012). Bikesharing across the Globe. City Cycling. MIT Press. UC Berkeley.

Teixeira, J. F., & Lopes, M. (2020). The link between bike sharing and subway use during the COVID-19 pandemic: The case-study of New York's Citi Bike. Transportation Research Interdisciplinary Perspectives.

White, H. (1980). A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. Econometrica, 817-838.

Appendix A

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

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

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

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:

$$L_t = \beta(\lambda_t + Bus_t + Metro_t + Tram_t) \quad (2)$$

$$with\ \beta > 1$$

Finally, from (1) and (2) we obtain the following formula for the outside option variable 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 each period $\boldsymbol{t}$.

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

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 the number of people living in the household

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