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ORIGINAL ARTICLE

Spatio-temporal patterns of the impact of COVID-19 on public transit: An exploratory analysis from Lyon, France

Benjamin Cottreau [1,2] | **Adel Adraoui** [1] | **Ouassim Manout** [1] | **Louafi Bouzouina** [1,3]

[1]LAET, ENTPE-CNRS-Université de Lyon, Vaulx-en-Velin, France

[2]Keolis Lyon, Lyon, France

[3]Open University, AT Heerlen, The Netherlands

Correspondence
Benjamin Cottreau, LAET, ENTPE-CNRS-Université de Lyon, 3 Rue Maurice Audin, 69120 Vaulx-en-Velin, France.
Email: benjamin.cottreau@entpe.fr

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Abstract

Public transit has been highly impacted by coronavirus disease 2019 (COVID-19), as well as transport demand in general. Using high-resolution data from smart card systems, this research investigates spatial and temporal variability of the pandemic's impact on public transit in Lyon, France. The study was conducted with a sample of 95,779 daily records, distributed over years (2019, 2020, and 2021) and public transit stops (520 bus rapid transit stops, 88 tramway stops, and 40 subway stops). Clustering and statistical methods are used to assess changes observed in the data. Findings highlight variability between modes in terms of intensity of impacts, recovery patterns, and stability of the shock over time. Results show that central areas recover worse than peripheral areas and west stops recover worse than east stops. Globally, effects of COVID-19 clear up over time, but not totally, with a faster recovery for subway. Local analysis on specific stops also suggests that public transit associated with medical facilities endures less COVID-19 impacts than employment zones or universities.

KEYWORDS
COVID-19, intensity, recovery, ridership, smart card, stability

JEL CLASSIFICATION
R40, R41, R48

1 | INTRODUCTION

Since the first official coronavirus disease 2019 (COVID-19) case in France on January 24th 2020, the French government, like many others, set up many restrictive policies. On March 17, 2020, the first lockdown was enforced, which implied strict limitations on travel, trip distance, and purpose. Non-essential activities were especially forced to close during this period, dramatically reducing reasons for mobility. In urban contexts, population density is a high-risk factor in terms of contamination and the spread of the virus. Closed areas, including public transit (PT), were particularly pointed to as serious contamination hot spots (Sharifi & Khavarian-Garmsir, 2020). Due to the global reduction of travel demand and a reduction in transit supply, an unprecedented and drastic drop in transit ridership has been recorded. In Lyon, the average drop in transit ridership during the first lockdown was nearly 100%. Since then, transit ridership recovered slowly. Nevertheless, patterns of decline and recovery of transit patronage seem to depend on the PT mode. Decline and recovery patterns of the subway, tramway, and bus rapid transit (BRT) are not similar. Figure 1 shows the normalized relative change in PT ridership for each week of 2020 and 2021 compared with 2019, and each of the three modes. Red stripes refer to lockdowns and other stripes colored with shades of orange refer to different periods of curfew. Aggregated values of PT ridership variations highlight a similar trend for the three modes. Change in PT ridership is mainly negative through both observed years, and strongly negative during lockdowns. Curfews seem to constrain PT ridership levels to a lesser extent. The fall observed in September 2020 corresponds to a week with a full day of strikes that had a huge impact on BRT lines, and therefore nothing to do with COVID-19 mitigation measures.

Timeline of main COVID-19 mitigation measures in Lyon :

- The first lockdown: from March 17, 2020 to May 11, 2020
- The first curfew (from 9 PM to 6 AM): from October 17, 2020 to October 29, 2020
- The second lockdown: from October 30, 2020 to December 15, 2020
- The second curfew (from 6 PM–9 PM to 6 AM): from December 15, 2020 to June 20, 2021
- The third lockdown: from April 3, 2021 to May 3, 2021

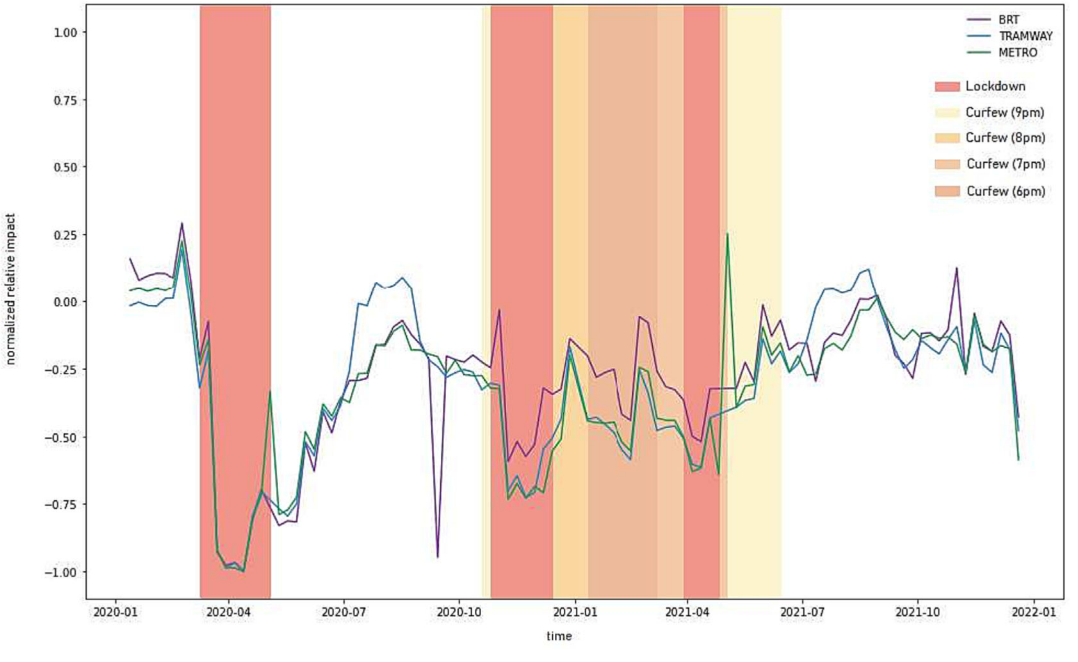


FIGURE 1 Relative evolution of public transit ridership in Lyon in 2020 and 2021 (ref.: 2019) per transit mode.

The impacts of COVID-19 on travel behavior have been abundantly studied in different spatial contexts, at different levels, and using different data sources and methodologies (Bouzouina et al., 2022). PT data are largely used at aggregated levels, such as regional (Jenelius & Cebecauer, 2020; Manout et al., 2023), or municipal (Aloi et al., 2020; El Zein et al., 2022; Gramsch et al., 2022) levels. These levels are often suitable for sociodemographic analysis, which combines activity or demographic data available for the same level of aggregation. Galeazzi et al. (2021) correlate node resilience of national PT network with gross domestic product (GDP) and population data in France, Italy, and the UK. They found a high correlation between resilience and wealth or density, but the contribution of these factors varies from one county to another. Spatial patterns are not further analyzed, but the assumption is that the structure of PT network and spatial planning policies can explain part of this variability. Carney et al. (2022) focus on elderly people who are often concerned with mobility exclusion issues, especially during the COVID-19 pandemic. They show evidence of spatial variability in terms of accessibility and frequency of use for this specific category. Astroza et al. (2020) used global mobility survey data, including several travel modes and household data, to identify population segments that are concerned with major mobility and working habits changes. They show variability between modes (PT presents the highest reduction compared with walking, car, or motorcycle) and user profiles (using socioeconomic factors such as income, gender, or employment status). Almlöf et al. (2021) used smart card data and sociodemographic data from Stockholm County to develop explanatory models for PT ridership during the pandemic. They notably used clustering to group areas with similar sociodemographic backgrounds and highlighted variability in PT use according to these clusters. Other studies also use smart card data analysis but at a higher spatio-temporal resolution. Mützel and Scheiner (2022) worked subway data from Taipei, Taiwan to reconstruct transit flows between stops for different time windows during weekdays and before and under COVID-19 restrictions. They demonstrate high spatio-temporal variability in subway ridership decline due to COVID-19. Similarly, Dueñas et al. (2021) worked on transit flows at several spatial levels: localities, zonal planning units, and transit stops. Results highlight socioeconomic variability, with high income being related with high mobility patterns before COVID-19 and lower income related with lower decrease in flow during and after COVID-19. Orro et al. (2020) studied bus demand in the city of Coruña in Spain at the line and stop levels, showing spatial variability in the drop observed for bus transit ridership during the pandemic. Among all the subjects that have been raised in relation to COVID-19, resilience is widely studied. Deschaintres et al. (2022) studied daily time series of PT demand and identified breakpoints, corresponding to the implementation of health policies. At a more disaggregated level, they compared different periods of the day and types of days. They highlighted that the highest decreases were observed during working days, at peak hours, and in the evening, therefore showing time variability of PT demand in response to COVID-19 shock. Dias et al. (2021) studied the contribution of e-scooters to overall mobility resilience during COVID-19. The paper shows that e-scooters can be a reliable option in terms of social distancing and sustainability in the post-COVID-19 era, and therefore contribute to urban mobility resilience to COVID-19 shock in demand. Stráuli et al. (2022) approaches the concept of resilience from a sociological point of view, using survey data from four different European cities. They define resilience as the "durability, transformability, and adaptability to changes in external factors as well as internal processes". High-resolution data available in our study allows us to quantify the notion of resilience and define suitable indicators that will help us to understand COVID-19 impacts on the transit system of Lyon.

The concept of resilience is often cited in the literature to characterize the ability of a system to get over an exogenous shock (Ahmed & Dey, 2020; Ganin et al., 2017). In the transportation context, it is often related to a shock in demand as observed in many situations, such as planned events that change the global structure of demand, or unplanned events, such as disruptions. Several indicators have been defined to measure resilience. Ahmed and Dey (2020) proposed a classification of most-used indicators, and some of them have been used to characterize COVID-19 impact on transit systems. Wang et al. (2022) used the concept of resilience triangle on subway data in relation to social attributes and compare PT during the three main phases of COVID-19 shock: reduction (in demand), growth, and stabilization. Their findings highlight group (commuters, elderly, and others) variability in subway system use. Xiao et al. (2022) used the concept of a short-term and long-term vulnerability of PT stops to create a resilience index on the basis of the Bayesian structural time series (BSTS) model. They also define resilience by two main aspects, which applied to our study, could be interpreted as the ability for a stop:

1. To maintain a level of demand close to pre-shock levels during the shock;
2. To consume the least amount of resources as possible (and among them, time is the most obvious and studied resource) to come back to pre-shock demand levels after the shock.

The existing literature indicates that COVID-19 has had a significant impact on PT and that different cities and systems are likely to have different resilience patterns. In this research, we measure the resilience of PT network by three indicators, all measured at the stop level:

- **Intensity** is a measurement of the magnitude of the impact of COVID-19 PT demand. It is associated with the first aspect of resilience previously described **(1)**.
- **Recovery** is defined as the ability for a stop to minimize COVID-19 shock over time, and retrieve pre-COVID-19 levels of PT demand. It is associated with the second aspect of resilience **(2)**, restraining resources only to time variable.
- **Stability** is defined as the ability for a stop to belong to the same group of stops that share common properties over time. It is an additional variable that helps to understand the evolution of PT structure over time.

In this paper, we address two research questions: What are the impacts of COVID-19 on PT ridership in Lyon? Are there spatio-temporal and modal variability regarding these impacts? This investigation is necessary to understand the resilience of PT toward shocks similar to COVID-19 and make suitable recommendations for transport policies and operational decisions. These recommendations can help to optimize transport services according to the new structure of demand.

This paper distinguishes itself from existing research in two main aspects. First, we compare several modes of the same PT system (subway, tramway, and BRT) using smart card data at the stop level. Using high spatio-temporal resolution data, we aim to see whether substantial differences in shock **intensity** exist between elements of the same urban PT system. Second, we compare two years (2020 and 2021) of data to define and assess concepts of **recovery** and **stability** of COVID-19 impact over time.

The paper is organized as follows. We introduce the methodology and data used in section 2. Next, results are shown and interpreted in section 3, then discussed in section 4. Section 5 concludes this research.

2 | METHODS AND DATA

Data used in this research are provided by Keolis Lyon, the local operator of the public transit system. These data include the total number of smart card validations for each day, at each PT stop, and for most transit modes (subway, tramway, and BRT). These data range from January 1, 2019 to December 31, 2021 (see Table 1a). In the following, the number of validations is referred to as PT demand or *dem*. The three transit modes are studied separately. In this section, data example are given using subway data.

2.1 | Assessment of shock intensity of COVID-19 using week-stop and stop clustering methods

The strengths of the clustering approach presented below lies in :

- The possibility to compare very different elements of a unique PT system, at a detailed spatio-temporal level, that is obtained from the normalization on days of the week and stops;
- The computational efficiency obtained from the chaining method;
- The simplicity to interpret outputs from HC method. Cut values used fix the number of clusters from the dendrogram and is a good measurement of data scattering. As every analysis is lead for each modes and each year (i.e., six different clustering algorithms are used), cut values are a good indicator for measuring variability between years and modes.

Table 1a presents demand (*dem*) for each day (identified by day of the week *d*, week *w*, and year *y*), as well as each stop (*s*). For each year (2019, 2020, and 2021), daily demand values are concatenated into week vectors of length 7. Weeks that have at least 1 day without data, and stops that have less than 60 weeks of data, are not considered. These records mainly correspond to stops that have been created or deleted during the studied period of time. Selected data include 520 BRT stops (76,475 records), 88 tramway stops (13,199 records), and 40 subway

TABLE 1a Samples taken from data frames used in this research. (a) Data frame of subway daily data.

Day (day)	Stop (s)	Demand (dem)
2019/01/01	LAURENT BONNEVAY	1883
2019/01/02	VIEUX LYON	5975
2019/01/02	MERMOZ PINEL	6119
...	...	...
2021/12/31	LAURENT BONNEVAY	5342
2021/12/31	MASSENA	5003

TABLE 1b Samples taken from data frames used in this research. (b) Yearly data frame of P_s vectors.

	P_s			
Stop (s)	$P_S(C_1)$	$P_S(C_i)$	...	$P_S(C_n)$
AMPERE	0.49	0.13	...	0.11
BELLECOUR	0.49	0.28	...	0.13
...	...	...	...	...
...	...	...	...	...
VIEUX LYON	0.66	0.27	...	0.06

TABLE 1c Samples taken from data frames used in this research. (c) Data frame of $I_{w,s}$ vectors.

			$I_{w,s}$						
Stop (s)	Year (y)	Week (w)	X_{MON}	X_{TUE}	X_{WED}	X_{THU}	X_{FRI}	X_{SAT}	X_{SUN}
AMPERE	2020	2	-0.025	-0.060	-0.073	0.056	-0.017	0.126	0.095
AMPERE	2020	3	0.016	0.033	-0.020	0.098	0.015	-0.011	0.094
AMPERE	2020	4	0.052	0.086	0.044	0.023	0.055	-0.124	-0.007
...	...	...	...	...	...	...	...	...	...
VIEUX LYON	2021	50	-0.175	-0.361	-0.006	-0.068	-0.001	0.058	-0.050
VIEUX LYON	2021	51	-0.178	-0.260	-0.201	-0.173	-0.201	-0.219	-0.027

stops (6,105 records). We use data from 2019 as a reference for the evaluation of the impact of COVID-19 on transit use. The public transit system of Lyon did not undergo any major change in 2019.

To compare different transit stops and lines that have different levels of use, data from each year are normalized using the $X_{s,y,w,d}$ function (Equation (1)). This function normalizes each observation (*y*) using 2019 as a reference year (*ref*) and a min–max scaling function. This normalization is applied to each stop (*s*) and each day of the week (*d*).

$$X_{s,y,w,d} = \frac{dem[s,w,d]_{ref} - dem[s,w,d]_{y}}{max_{s,d}\left(|dem[s,d]_{ref} - dem[s,d]_{y}|\right)} \tag{1}$$

For each year, $X_{s,y,d}$ are combined into stop-week data using Equation (2). An example of the resulting vectors is presented in Table 1c. The dataset includes 95,779 records that will be used to investigate the impact of COVID-19 on transit use in Lyon. Due to the massive amount of data available, we rely on clustering methods to unveil similarities and dissimilarities between stops and weeks. As stop-week data clustering is performed independently for each year, we will use the simplified notation $I_{w,s}$.

$$I_{\mathrm{w,s}} = \left[X_{s,y,w,d=MON}, X_{s,y,w,d=TUE}, \ldots, X_{s,y,w,d=SUN}\right] \tag{2}$$

To assess the intensity of the shock of COVID-19 on transit patronage, stop-week vectors are clustered to find similarities between them. Clustering of stop-week vectors is performed by chaining K-means and hierarchical clustering (HC) methods (Cats & Ferranti, 2022; Viallard et al., 2019):

- **Step 1**: $I_{w,s}$ vectors are clustered using the K-means algorithm for each year (2020 and 2021). The method used for this clustering is ward algorithm with Euclidean metric. For this clustering, a high number of clusters is chosen. Resulting cluster centers are then used as input cluster for the second step;
- **Step 2**: Intermediate cluster centers are clustered using HC technique with the same algorithm and metric as step 1. Final clusters are chosen on the basis of a threshold value of variance that better cuts the dendrogram. Final cluster centers are shown in Figure 2.

An advantage of this method is that it analyzes cluster memberships in time and for each stop. Resulting proportions $\mathrm{P_s(c_k)}$ of cluster $\mathrm{c_k}$ are used to create a profile for each stop (*s*) and stored in vector $\mathrm{P_s}$ (Table 1b). Stop vectors are then clustered using the HC method to group similar stop profiles and compare their temporal and spatial distributions within the public transit network. By using the same method, monthly proportions $\mathrm{P_m}$ are calculated for each month *m* and shown in Figure 3.

2.2 | Stability and recovery of stops using yearly growth rate

For the study of *Stability* and *Recovery*, we use the relative change in transit use per stop and per year, with 2019 being the reference year (Equation (3)). This simple indicator computes the global evolution of demand since it smooths temporary variations. To this end, we keep the same number of weeks in each year for each stop, by checking that week (*w*) exists for the 3 years of data.

$$G_y(s) = \frac{dem[s]_y - dem[s]_{ref}}{dem[s]_{ref}} \tag{3}$$

Recovery is defined as the ability of a stop to retrieve its pre-COVID-19 levels of transit demand. Looking at intensity measurements over time helps to understand the dynamics of recovery (e.g., is it a short-lasting or long-

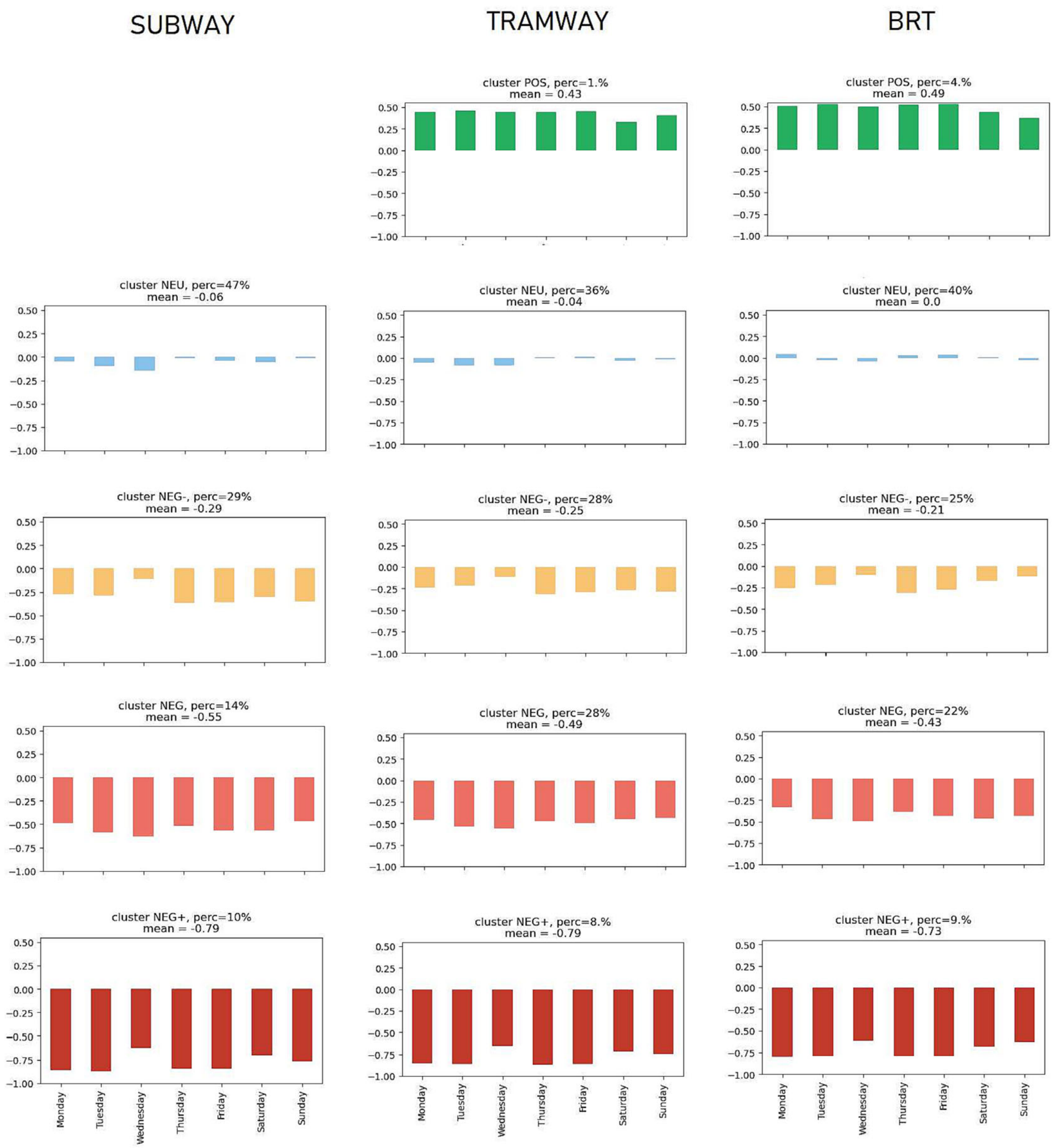


FIGURE 2 Stop-week cluster centers (based on $I_{w,s}$ normalized impact vector).

lasting recovery?). However, we may need an aggregated indicator that helps to more directly assess this notion of recovery. To have a measurable definition of recovery (i.e., not only referring to cluster memberships, which is a relativistic approach of the magnitude of COVID-19), we have decided to use the yearly growth rate. This gives a clear and direct percentage of PT demand evolution during the observed years (2020 and 2021) and the reference year (2019). For a stop, perfect recovery would be that its demand in 2020 or 2021 is at least equal to that of 2019. Nevertheless, this scenario is observed in very few cases. To be able to assess recovery patterns, 2020 and 2021 growth rates have been compared: if $G_{2021}(s)$ is superior to $G_{2020}(s)$, then stop s would be considered on its way to recovery. Otherwise, stop s would be considered as not recovered.

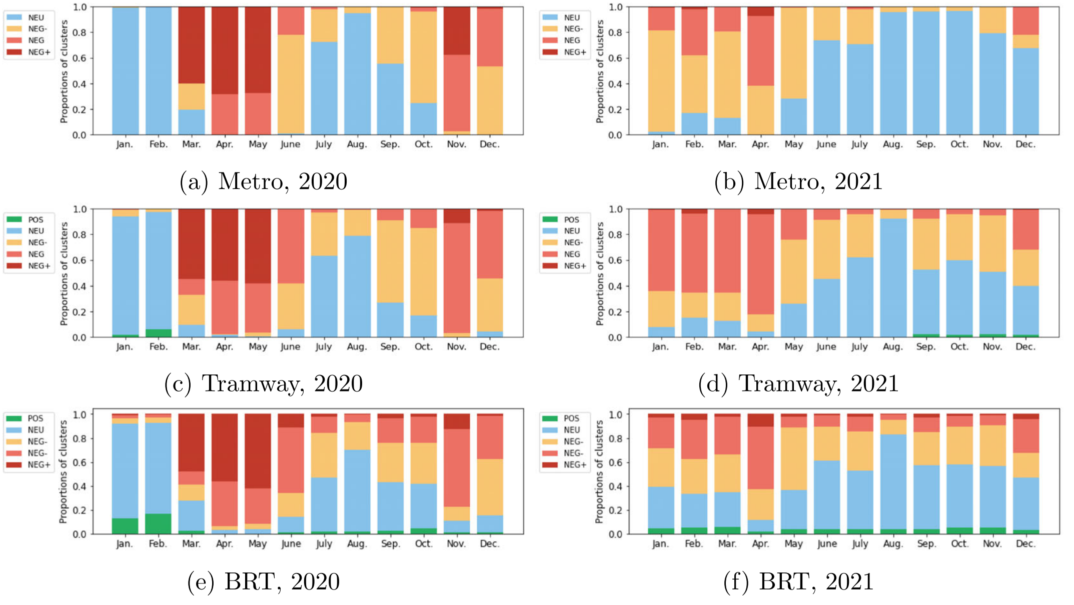


FIGURE 3 Monthly cluster membership using proportions P_s.

Stability is defined as the ability for a stop to belong to the same group of stops that share common properties over time. To be able to compare stations, we then need to fix a framework in which stops become comparable. Clustering methods aim to minimize the intra-group variance and highlight similarities between stops. However, comparing cluster membership from one time step to another can be tricky, as all group properties change over time (number of elements, mean, variance, etc.). In the following analysis, we use interquartiles to fix the number of observations per group. Therefore, by analyzing stop membership to interquartiles from 2020 to 2021, we will be able to objectify our analysis of stability. This notion of stability helps to understand the inner structure of PT subsystems (i.e., modes). A first hypothesis could be that a global shock has an evenly distributed effect on every element of a PT system, and stops recover to the same extent over time. In this case, the PT system would be considered as very stable and global policies considering the whole system should be taken. A second hypothesis could consider that PT systems show more entropy. In this case, recovery scenarios are more variable and the whole PT system is less stable regarding its response to COVID-19 shock. PT policies should take local actions at the stop level to tackle its individual trajectory of recovery.

3 | RESULTS

3.1 | Spatio-temporal patterns of the impact of COVID-19 on transit

Figure 2 shows, for each transit mode, the retained clusters that depict distinctive patterns of the impact of COVID-19 on transit use. Clusters have been named after the impact magnitude. Since data are normalized, cluster centers can be compared between modes. We characterize the impact patterns by five categories: strong negative impact or *NEG+* (impact between -100% and -60%), negative or *NEG* (impact between -60% and -40%), slightly negative or *NEG-* (impact between -40% and -10%), neutral or *NEU*(impact between -10% and +5%), and positive or *POS* (impact between +5% and +50%). The impact of COVID-19 on the subway system can be described by four clusters ranging from NEG- to NEU. The impact of COVID-19 on the tramway and BRT can be described by five clusters each (Figure 2).

The analysis of cluster memberships (Figure 2) suggests that the impact of COVID-19 in 2020 and 2021 was the highest on the tramway. A total of 64% of tramway data fall within the negative clusters (NEG+, NEG, and NEG-). The subway and BRT systems have a lower share of validations within these clusters (53% for the subway and 56% for the BRT). The discrepancy between transit modes is even substantial if the analysis is limited to the NEG+ and NEG clusters. In total, 36% of tramway data fall within these two clusters. This share is of only 24% and 31% for the subway and BRT systems, respectively.

Regarding daily impact, clusters NEG+, NEG, and NEG- have similar impact patterns for all modes. NEG+ shows that Wednesdays and weekends are less impacted than the rest of the weekdays. NEG- shows that Wednesdays are less impacted. For the NEG cluster, Mondays and Thursdays are less impacted.

3.1.1 | Timeline of the shock of COVID-19 on transit use

All modes seem to follow the same trend during the 2 years (Figure 3). However, some differences can be observed according to clusters that exist or not for each considered mode. Similarities and differences observed in time are the following:

- **Before the first lockdown (January to February 2020)**, the *NEU* cluster was predominant for the subway and tramway. BRT attracted more users during that period than during 2019. A total of 15–20% of its weeks belonged to the *POS* cluster.
- **During the first lockdown (March to June 2020)**, negative clusters were predominant during that period. Cluster *NEG+* was the most representative of the period (maximum share between 70% and 60% depending on the mode). During lockdown months, especially April and May, most of the observations fell within *NEG* and *NEG+* clusters for the three modes.
- **The second lockdown (October to December 2020)** shows a similar trend to the first lockdown period, except that the *NEG* cluster was more predominant than the *NEG+* cluster. This change means a decrease in the intensity of the shock of COVID-19. In the descending order of impact, we find the subway, the tramway, then the BRT.
- **Comparing the third lockdown (April 2021)** with the second lockdown, the *NEG* cluster was clearly predominant compared with the *NEG+*. The shock on demand was temporarily less intense, as people got used to the "new normality" rules. Mode trends show that the tramway was the most impacted mode, followed by the subway, then the BRT.
- **The first curfew (October 2020)** lasted 12 days and was followed by the second lockdown. It was characterized by an increase in the share of *NEG-* and *NEG* clusters in October for all modes.
- **The second curfew (December 2020 to June 2021)** had several phases with different forms of restrictive rules, especially in various time windows from December 2020 to June 2021, including the third lockdown in April 2021. Before the third lockdown, observations fell mainly within the negative clusters, and among them, *NEG* is the most representative for the tramway and *NEG-* for the subway and BRT. After the third lockdown, *NEU* and *NEG-* shares were predominant. This change corresponds to a relaxation of the curfew limitations and the end of all restrictive rules in June, which explains the diminution of shock intensity. The tramway and BRT showed a long-lasting presence of the *NEG-* cluster.
- **Each year, summer holidays (July and August)** are characterized by a diminution of the intensity of the shock with the resurgence of the *NEU* cluster. The drop in subway ridership was less intense than for the tramway or BRT.

The intensity of the shock of COVID-19 on transit use was heterogeneous and it varied in time and according to the transit mode. Its deepest impact was observed during the first curfew, which matched with the observation of Figure 1. The intensity of the shock caused by restrictive lockdowns then decreased over time. PT users gradually got along with the "new normality" rules and got back to using transit. Nevertheless, the long periods of night curfews had a long-lasting impact on demand, especially for the tramway and BRT. The global trend shows that none of the modes had recovered perfectly from COVID-19.

On the one hand, NEG+ is predominant when lockdown occurs. The intra-week pattern of NEG+ shows that Wednesdays and weekends are less impacted than other weekdays. This can be explained by the fact that PT ridership during these is lower during the reference year, as is the intensity of the shock during observed years (i.e., PT are originally less used during these days, and the trend is confirmed during lockdowns). On the other hand, NEG- is predominant during curfews and shows particular intra-week patterns compared with NEG+ (Mondays and Thursdays are less impacted than other days). This reveals singular mobility trends during these periods: this observation can be related to working from home, which is expected to be higher when this kind of mitigation measures are implemented. Therefore, the classic intra-week pattern is replaced by a more adaptive pattern, where Mondays and Thursdays seems to be favored (people tend to choose these days to go to the office) compared with other weekdays (that are more suitable for work from home).

Differences between modes in terms of the impact intensity are noteworthy: the tramway endures a deeper and longer-lasting shock than other modes. To a lesser extent, the impact on the subway is comparable to that of the tramway, except that the *NEU* cluster was predominant for the subway by the end of 2021, which suggests a better recovery. The impact on BRT was the least intense, as the cumulative shares of the *POS* and *NEU* clusters are the highest of all modes during the shock periods. However, the long-lasting presence of *NEG* and *NEG+* clusters for the BRT suggests a modest recovery in comparison with the other modes.

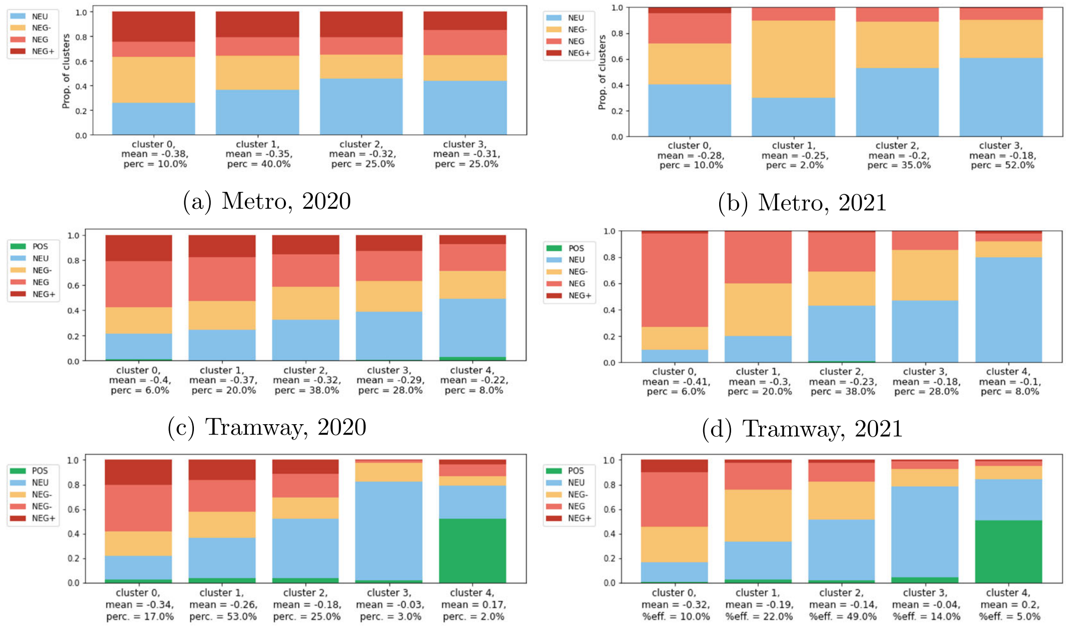
3.1.2 | Spatial distribution of the shock of COVID-19 on transit use

For each transit stop and each mode and each year (2020, 2021), a second clustering is performed with the share of clusters as input data (from NEG+ to POS). Cluster centers for each mode are shown in Figure 4. For each cluster center, the mean impact has been calculated and new clusters have been ordered thanks to this measure, from the highest (cluster 0) to the lowest (up to cluster 4) impact.

Between 2020 and 2021, the *NEG+* share decreased from 20% to less than 10% in most impacted clusters, across all modes. As seen in the temporal analysis, this decrease is explained by the fact that 2020 contains weeks from the first lockdown, which largely belong to the *NEG+* cluster. 2021 contains curfew and shorter lockdown periods, during which PT users moved less restrictively. Meanwhile, the cumulative shares of the *NEU* and *POS* clusters increase, globally, for both years.

In the following subsections, an empirical spatial framework is set up to ease the analysis of our results (Figure 5). It will be used to aggregate data from the stop level to broader groups of stops :

- **Central stops** correspond to stops located in the first or second districts of Lyon, or in an area defined by Rhône river in the west, Parc Tête d'Or in the north, Part-Dieu train station in the east, and Jean Macé train station in the south (Figure 5).
- **Transfer stops**, which are stops where at least two lines of the same mode pass by. In the case of the tramway, whole parts of lines are shared between several lines. We decided to pick up the first and last stops of these parts of lines and consider them only as transfer stops. BRT transfer stations are implemented when a BRT line stops at a subway station. It concerns 28 subway stops out of 40.
- **East stops** correspond to all stops that are not transfer stops or central stops, on the east side of Rhône river.
- **West stops** correspond to all stops that are not transfer stops or central stops, on the west side of Rhône river. This area is hilly and thus less accessible by heavy PT (tramway or subway). This area is mainly served by the BRT and conventional bus lines.



(a) Metro, 2020 (b) Metro, 2021

(c) Tramway, 2020 (d) Tramway, 2021

(e) BRT, 2020 (f) BRT, 2021

FIGURE 4 Cluster membership of stops in 2020 and 2021 using proportion $P_s(c_k)$.

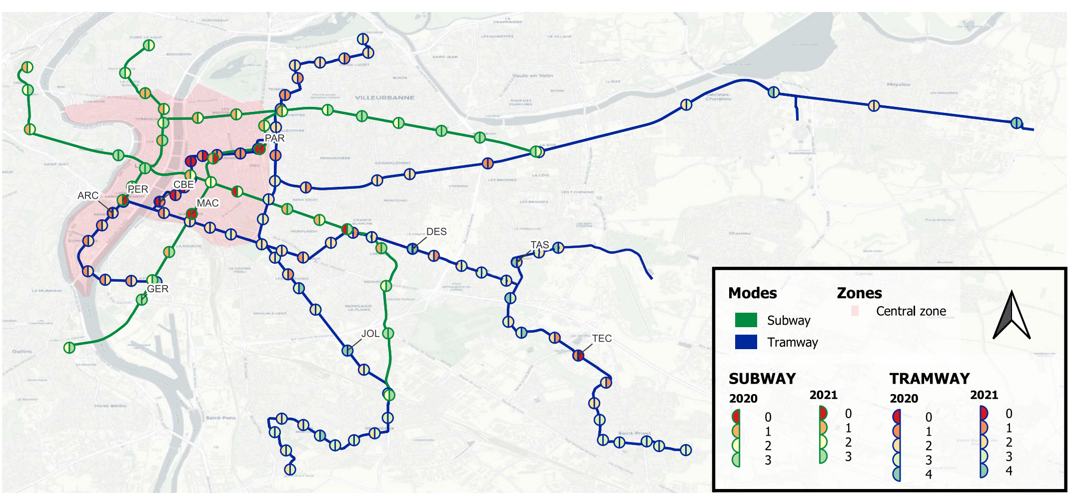


FIGURE 5 Map of clustered subway and tramway stops in 2020 (left-hand symbols) and 2021 (right-hand symbols).

Stop clustering allows to group stops that have a similar impact pattern with regard to the impact of COVID-19. Figure 5 shows the spatial distribution of stop clusters. For each stop, clusters of 2020 and 2021 are displayed on the left-hand and right-hand sides, respectively.

Subway: Thresholds chosen to cluster stops thanks to HC dendrograms are 0.25 for 2020 and 0.35 for 2021, which first demonstrates there is more variability in 2021 relative to 2020. For each year, four clusters are retained, numbered from 0 (highest impact) to 3 (lowest impact). These thresholds are quite low compared with other modes, which means that the total sample variance is low, and therefore stop profiles are very similar. In 2020, cluster centers from clusters 0 to 2 have an increasing proportion of *NEU* clusters (up to 40%). Cluster 3 shows a decrease of *NEG*+ to the benefit of the *NEG* cluster. In 2021, the *NEG*+ cluster belongs only to cluster 0. Clusters 1–3 are characterized by a resurgence of the *NEU* cluster.

Including both years, the results from stop clustering (sorted percentages are given) are as follows. We count 12 central stops, 4 transfer stops, 17 eastern stops, and 7 western stops:

- **Cluster 0**, which stands for the most impacted stops, is composed of central stops (87%) and eastern stops (13%).
- **Cluster 1** is composed of central stops (47%), east stops (24.5%), western stops (24.5%), and transfer stops (6%).
- **Cluster 2** is composed of eastern stops (33%), central stops (29%), western stops (21%), and transfer stops (17%).
- **Cluster 3**, which stands for the least impacted stops, is composed of eastern stops (68%), western stops (16%), transfer stops (10%), and central stops (6%).

Central stops are the most impacted by COVID-19. More than half of them belong to clusters 0 or 1, while other spatial groups have less than 30% of stops belonging to these clusters. Transfer and eastern stops are the least impacted by COVID-19. More than 75% of these stops belong to clusters 2 or 3. Western stops are in an intermediate position, with 29% and 35.5% of the stops belonging to clusters 1 and 2, respectively, and 35.5% to cluster 3.

Two findings are noteworthy:

- Stops that allow transfers with train stations in the city center (Perrache [**PER**], Part-Dieu [**PAR**], and Jean Macé [**MAC**]) are more likely to belong to clusters 0 or 1. National or regional connections are a factor of the discrepancy in the impact of COVID-19.
- Terminus stops, and more generally those located at the end of a line, are more likely to belong to the less impacted clusters.

Tramway: Thresholds chosen to cluster stops thanks to HC dendrograms are 0.75 for both 2020 and 2021, which shows a relative uniformity compared with other modes. We end up with five clusters in each case, numbered from 0 (highest impact) to 4 (lowest impact). These thresholds are 2–3 times higher than the subway, which means a relatively higher variability compared with this mode. In 2020, cluster center proportions of the *NEG*+ and *NEG* clusters range from 60% (cluster 0) to 25% (cluster 4). In 2021, the *NEG*+ cluster is almost absent and the *NEG* cluster share varies from 70% (cluster 0) to 5% (cluster 4).

Including both years, the results we get from stop clustering (sorted percentages are given) are as follows. We count 13 central stops, 8 transfer stops, and 60 eastern stops:

- **Cluster 0** is composed of central stops (90%) and eastern stops (10%).
- **Cluster 1** is composed of eastern stops (47%), central stops (36%), and transfer stops (17%).
- **Cluster 2** is composed of eastern stops (83%), transfer stops (11%), and transfer stops (6%).
- **Cluster 3** is composed of eastern stops (94%) and transfer stops (6%).
- **Cluster 4** is only composed of eastern stops.

Similar to the subway, central stops are the most impacted by COVID-19: 85% of tramway stops belong to clusters 0 and 1. Eastern stops are the least impacted, as they are the exclusive members of cluster 4 and quasi-exclusive members of cluster 3. In between, transfer stops mostly belong to clusters 2 (38%) and 3 (44%).

Regarding tramway data, the main results are:

- Central stops from Université Claude Bernard [**CBE**] to Part-Dieu [**PAR**] train station have the highest drop during both years. In 2020, they all belong to clusters 0 or 1. Many jobs (mainly from the service sector) are located in this zone. Furthermore, one of the most important universities is also located in this area. These two factors (employment and educational facilities) seem to play a role in the drop in demand.
- Marginal drop in demand is observed at the edge of the tramway lines. However, Parc Technologique [**TEC**] stop shows a significant drop in 2020 and 2021. This stop serves mainly for commuting to and from the corresponding employment zone.
- Low decline in demand is observed near medical facilities (Vinatier, Edouard Herriot, and Desgenettes hospitals, [**DES**]), and supermarkets [**JOL**], which could be explained by the continued use of these facilities during the COVID-19 pandemic.

BRT: Thresholds chosen to cluster stops thanks to HC dendrograms are 1.5 for 2020 and 1.8 for 2021, which demonstrates the higher variability in the impact of COVID-19 during 2021 relative to 2020. Five clusters are retained, numbered from 0 (highest impact) to 4 (lowest impact). These cut thresholds also show relative heterogeneity in comparison with the subway and tramway. In 2020, cluster center proportions of *NEG+* and *NEG* clusters ranges from almost 60% (cluster 0) to less than 5% (cluster 3). Cluster 4 contains a few stops that have a majority of *POS* weeks. In 2021, the maximal share of the *NEG+* cluster is 5%. The share of the *NEG* cluster varies between 45% (in cluster 0) to less than 5% (in clusters 3 and 4).

Including both years, the results we get from stops clustering (sorted percentages are given) are as follows. We count 56 central stops, 29 transfer stops, 205 western stops, and 231 eastern stops:

- **Cluster 0** is composed of western stops (47%), eastern stops (38%), central stops (10%), and transfer stops (5%).
- **Cluster 1** is composed of eastern stops (46%), western stops (34%), central stops (13%), and transfer stops (7%).
- **Cluster 2** is composed of eastern stops (43%), western stops (39%), central stops (12%), and transfer stops (6%).
- **Cluster 3** is composed of eastern stops (51%), western stops (36%), central stops (7%), and transfer stops (6%).
- **Cluster 4** is composed of eastern stops (64%), western stops (27%), central stops (4%), and transfer stops (5%).

The distributions of BRT stops among clusters is balanced compared with other modes. Looking at the results from the spatial perspective, there is no clear pattern. One can argue that western stops are more impacted than other stops, as 27% of them belong to clusters 0 (against 20% for other zones), and eastern stops are less impacted, as 24% of them belong to clusters 3 or 4 (against less than 20% for other zones).

A global geographical pattern exists, showing that the intensity of the shock of COVID-19 on PT demand is slightly higher is the western side than on the eastern side. Socioeconomic factors could explain this output, as each of these zones corresponds to population profiles with specific attributes in terms of wages, car ownership levels, or socioeconomic status. Several studies have shown the predominance of these factors in the ability to work from home (Dueñas et al., 2021; Falkenberg et al., 2020). Further studies could be carried out to tackle this issue from an explanatory perspective. Variability between modes is also observed: the impact is higher for subway and tramway central stations than for peripheral stations. This result could be explained by the fact that location of activity in central areas is very close to each other, which allows for PT to be easily replaced by cheaper modes, during periods of time without mitigation measures or with less restrictive mitigation measures. However, distance to activity or employment rises as we move to peripheral areas, and therefore mobility is more constrained, which can explain that these PT stops endure COVID-19 shock better than central stops. This result does not hold true for the BRT. Variability within modes is also observed: the spatial distribution of BRT clusters is nearly uniform. For tramway and subway stops, a clear spatial distribution is found. This can be explained by the structure and ridership of each transit mode. The subway and tramway are more heavy transit systems with higher use and few stations compared with the BRT.

3.2 | Recovery and stability

3.2.1 | Aggregated recovery analysis

Stops have been aggregated according to two different levels:

- **An empirical spatial aggregation**, based on our knowledge of the territory. Stops have been grouped into four main classes, as defined at the beginning of Section 3.1.2;
- **An aggregation of stops by line**. In this case, when a stop belongs to two different lines, it is duplicated as many times as the number of lines serving it.

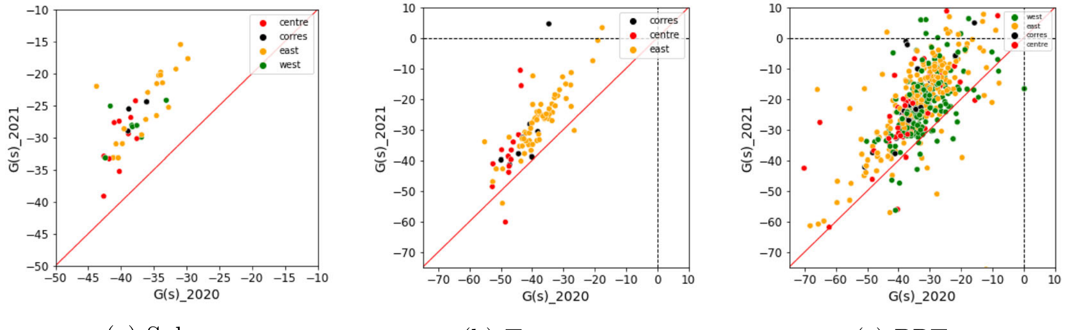
Stops are displayed in a graph showing the relationship between G_{2020} and G_{2021}. Different levels of aggregation are shown with different colors, and line $y = x$ is also displayed (Figures 6 and 7).

Subway: shows meaningful spatial patterns (Figure 6a): from the highest to the lowest decline, central stops come first, then western stops, transfer stops, and eastern stops. Their respective barycentric coordinates are [-40%, -31%], [-38%, -28%], [-38%, -27%], and [-36%, -25%]. All subway stops have an average impact that is lower in 2021 than in 2020, which suggests a global recovery for this mode.

From the line aggregation perspective (Figure 7a), lines A [-37%, -25%] and D [-37%, -26%] show a better recovery than lines B [-39%, -29%] and C [-40%, -31%]. Interestingly, Part-Dieu [**PAR**: -43%, -39%] is the stop that recovers the least, which is a shared characteristic of the tramway stop. This result suggests that specialized employment zones suffer particularly from COVID-19 effects, partly due to remote work.

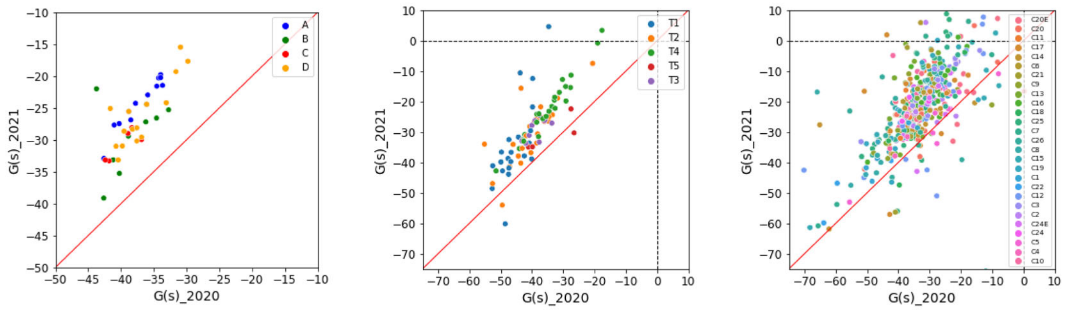
Tramway: Empirical aggregation shows a substantial spatial pattern with tramway data (Figure 6b). The tramway has no western stops. Eastern stops recover better than transfer stops and central stops. Their respective barycentric coordinates are [-37%, -27%], [-42%, -30%], and [-47%, -37%]. From the line aggregation perspective (Figure 7b), tramway lines T4 [-36%, -23%] and T5 [-35%, -28%], located in the eastern part of the city, have a better recovery pattern than other lines. Conversely, tramways T1 [-45%, -34%] and T2 [-40%, -29%], whose stops are located in the central area, recover the least from COVID-19. Tramway line T3 [-39%, -30%], which serves the eastern side of the city, has similar barycentric coordinates to the T2 line, but its stops are mainly located in the middle of the graph (Figure 7b). The impact of COVID-19 on transit ridership of T3 stops is more homogeneous than for other lines.

A total of 97% of tramway stops show a lower drop in demand in 2021 than 2020, which proves a good global recovery of tramway ridership. Three stops do not recover: Part-Dieu [**PAR**: -49%, -60%] and Parc Technologique [**TEC**: -50%, -54%] are the two stops that recover the least, and De Tassigny - Curial [**TAS**: -27%, -30%] has growth factors closer to the whole sample mean. Part-Dieu [**PAR**] and Parc Technologique [**TEC**] are among the most



(a) Subway (b) Tramway (c) BRT

FIGURE 6 Evolution of the growth factor for each stop from the zone aggregation perspective.



(a) Subway (b) Tramway (c) BRT

FIGURE 7 Evolution of the growth factor for each stop from the line aggregation perspective.

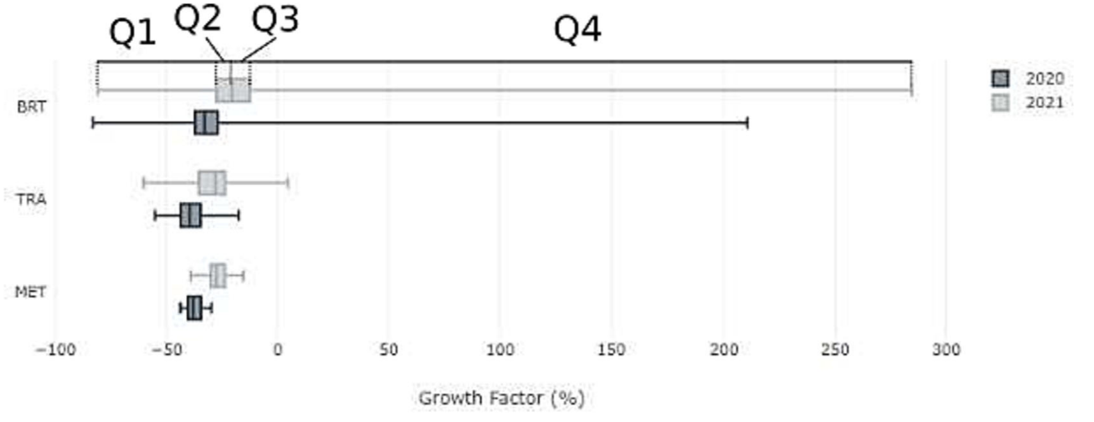


FIGURE 8 Boxplots of growth factor (G_y) per year and mode.

important employment zones in Lyon, which again suggests that stops used mainly for commuting to work are likely to recover less from COVID-19 in comparison with other stops located in areas with more mixed land uses.

BRT: A total of 93% of BRT stops have a lower drop in demand in 2021 than in 2020, which means an overall recovery of the BRT network, a recovery that is close to that of the tramway. Patterns shown in Figure 6c and 7c are consistent with previous results that demonstrate a broad distribution of BRT data, and therefore a high variability in the recovery patterns. Therefore, spatially grouping BRT stops does not reveal any spatial correlation.

3.2.2 | Stop stability over time

Groups, i.e., interquartiles, are identified in Figure 8 for each mode. First, it is noteworthy that the variability (i.e., range from minimum to maximum value) of the impact is higher in 2021 than in 2020 for all modes. PT modes also have different variability values. In the descending order, we find the BRT, then the tramway, and finally the subway. BRT stops have the highest range for one interquartile (i.e., Q4). This is due to a limited number of stops that have high growth factor changes in 2020 and 2021. Only 2% of BRT stops in 2020 and 5% in 2021 have growth factors higher than 10% (compared with none for the subway and the tramway). Therefore, BRT variability is skewed by these exceptional cases. Results suggest that mode variability is related to the level of ridership of the mode.

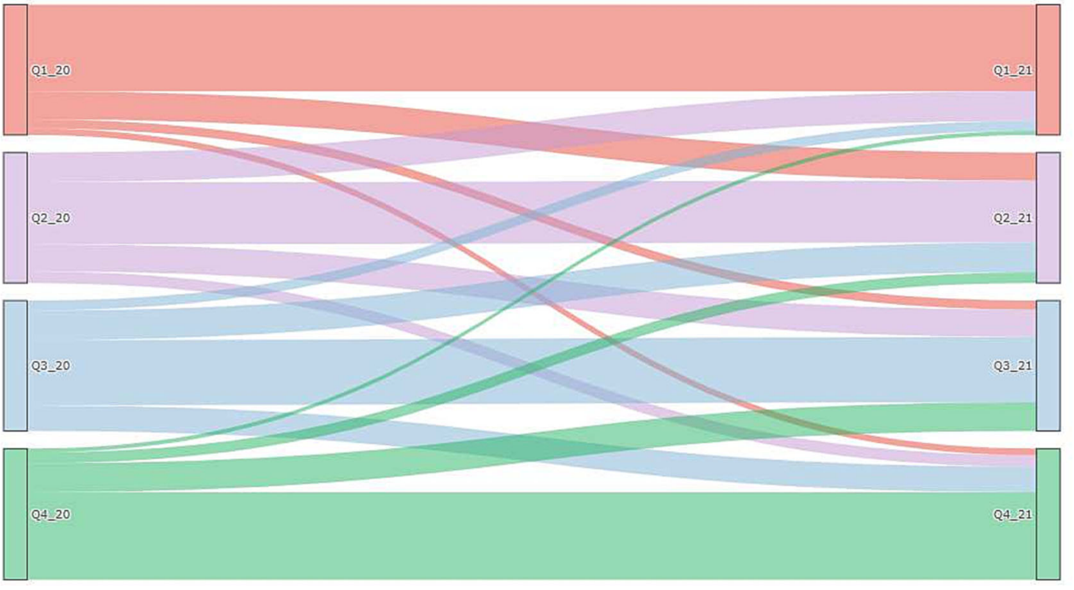


FIGURE 9 Sankey diagram showing the relation between groups of stops (interquartiles) in 2020 and 2021 for all modes.

When comparing 2020 and 2021, 58% of stops belong to the same interquartile. This suggests a certain stability of the impact of COVID-19 impacts at the stop level. More especially, extreme interquartiles Q1 (highest decline) and Q4 (25% lowest decline) are more stable than the others, with 66% and 67%, respectively, of stops in 2020 that are in the same group in 2021. Q2 keeps 47% of stops in 2021, while Q2 keeps 50%. In most cases, transfers are made between interquartiles Qn and Qn+1 or Qn-1 (22% on average), but also between Qn and Qn+2 or Qn-2 (8% on average). Transfers between Q1 and Q4 are rare (4% on average). Evidence of these transfers for all modes are shown on a Sankey diagram (Figure 9). The following analysis deals more precisely with stability mode by mode.

All three modes are globally stable: the tramway (73%) is more stable than the subway (60%) and the BRT (57%).

Extreme interquartiles: by looking at the intra-mode stability, interquartile Q1 is more stable for the tramway (77%) than the subway (70%) and the BRT (64%). Interquartile Q4 is more stable for the subway (80%) and the tramway (77%) than the BRT (64%). One stop falls from Q4 into Q1 in the case of the subway (Gerland, [**GER**]) and the tramway (Place des Archives, [**ARC**]). Five BRT stops show a particularly good recovery, by moving from Q1 to Q4, and six BRT stops move from Q4 to Q1. Among these stops, there are no significant geographical or line patterns.

Middle interquartiles: the tramway is again the most stable mode (Q2: 59%, Q3: 77%), whereas the subway (Q2: 50%, Q3: 40%) and the BRT (Q2: 45%, Q3: 46%) have similar values that show they are less stable.

Effects of COVID-19 on PT demand at the stop level are globally stable over time. However, stability is not uniform among transit modes. The tramway is more stable for each of the four interquartiles than other modes. The subway is relatively less stable than the tramway, but shows more stability than the BRT.

4 | DISCUSSION

Intensity: Variability between modes is found regarding the intensity of the impact of COVID-19 on ridership. Subway stops have very similar profiles, meaning that the subway system response is uniform (Mützel & Scheiner, 2022). Comparatively, COVID-19 impact patterns of the tramway are three times more diversified, and BRT six times more diversified, which is consistent with results found by Orro et al. (2020) for bus transit. PT ridership has experienced a significant discrepancy during the first lockdown. This study shows that the tramway suffers more intensively from COVID-19 than the subway or the BRT. The tramway and BRT have long-lasting impacts, while the subway does not show such trends, recovering faster at the end of the restriction period. Intensity analysis at the stop level highlighted some stops as being specifically more impacted than others within the same line or mode. This is the case of commuting stops (work or education). Conversely, less decline has been found near hospital facilities. Other studies have shown that PT at university stops (Bagdatli & Ipek, 2022; Orro et al., 2020; Szczepanek & Kruszyna, 2022) or in business areas (Mützel & Scheiner, 2022) are hardly hit by COVID-19, whereas stops close to hospital facilities have lower impacts (Orro et al., 2020). In another context, these results related to employment zones are consistent with the case of Melbourne, where Currie et al. (2021) observed a decrease in commuting trips, which benefits car use in the central business district. Weekly patterns show that Wednesdays are globally less impacted than other working days. This is in line with findings from Manout et al. (2023). In the French context, Wednesday is significantly used as a day off in part-time jobs or for in working from home, which explains why pre-COVID-19 levels of demand were originally lower than other working days and thus the impact of COVID-19.

Recovery: The subway is on the road to recovery, as 100% of its stops have a higher demand in 2021 than in 2020. From this perspective, the tramway (97%) and the BRT (93%) recover the least. Recovery shows specific spatial patterns: this study demonstrates that central stops are globally the most impacted and struggle more to retrieve pre-COVID-19 levels. There is also an opposing pattern between western and eastern stops, with eastern stops recovering better than western stops. The analysis of transfer stops does not show significant patterns. The BRT shows less significant spatial patterns at our level of analysis; the spatial zoning we use might bias this result since it is too coarse to characterize the full variability of stop profiles that exist in the BRT network. Given this, recovery of the BRT is slightly better in the eastern part than in the west. Dueñas et al. (2021); Almlöf et al. (2021) and Astroza et al. (2020) have demonstrated that underprivileged people continued to use transport during COVID-19. Conversely, users with higher incomes used less PT since they can more easily work from home or opt for other individual means of transportation. As evidence of spatial segregation has already been shown in terms of socioeconomic profiles in Lyon (Bouzouina et al., 2021), further analysis should investigate the link between spatially varying impact, land use (space function), and sociodemographic data. El Zein et al. (2022) demonstrated the correlation between the drop in PT use in Lyon and the possibility to work from home or choosing an alternative mode in Lyon.

Stability: the PT system is globally stable, as the majority of stops belong to the same statistical groups in 2020 and 2021. Even though variability in the impact intensity has been shown in this paper, this result shows that the global trend of recovery observed is quite uniform among stops and over time. Nevertheless, disparities are observed among modes, with the tramway being the most stable (73%), followed by the subway (60%) and the BRT (57%). Stability analysis can give insights for public policies to take local actions on specific stops. For instance, dealing with the five BRT stops moving from Q1 to Q4, the reason of such a behavior should be tackled with a specific study, questioning whether to maintain these stops. Similarly, stops moving from Q1 to Q4 should be analyzed questioning their sizing and the type of infrastructure associated with them. For more stable modes such as the tramway, it is appropriate to have a global approach, trying to adapt the offer to the new demand induced by COVID-19 shock at the line level. This can be done by revising time schedules and frequencies associated with this line.

TABLE 2 Modes ranking regarding to intensity, recovery, and stability.

	SUBWAY	TRAMWAY	BRT
Intensity	Short-lasting (2nd)	Long-lasting (1st)	Long-lasting (3rd)
Recovery	Spatially consistent (1st)	Spatially consistent (2nd)	Little spatial consistency (3rd)
Stability	Stable (2nd)	Very stable (1st)	Stable (3rd)

5 | CONCLUSIONS

This paper addresses the following questions: *What is the impact of COVID-19 shock on demand for urban public transit? Is there spatio-temporal and modal variability regarding this shock?* Findings demonstrate variability between modes, space, and time for PT in Lyon. Table 2 summarizes the findings by sorting modes according to the three factors considered: intensity, recovery, and stability. First, in terms of **intensity**, the tramway is the most impacted mode (1), followed by the subway (2) and the BRT (3). The intensity of the shock lasted longer in the case of the tramway and the BRT. For both years, the intensity is also more uniform for the subway than the tramway or the BRT. Second, in terms of **recovery**, the subway recovered better (1), followed by the tramway (2) and the BRT (3). Spatial patterns are very consistent for the subway and tramway. The BRT shows less obvious patterns. The findings highlight that central stops recovered less than other stops. Eastern stops recovered better than western stops and no significant conclusion can be drawn for transfer stops. Finally, in terms of **stability** of impacted stops between 2020 and 2021, the tramway is the most stable mode (1). The subway (2) and the BRT (3) are significantly less stable than the tramway.

The study of intensity at different temporal levels highlights that ridership levels are different depending on the mitigation measure implemented on a certain period of time. A monthly aggregated approach shows the global drop in PT transit: this provides a large-scale understanding of COVID-19 impact. This analysis is useful for operators to understand the depth of impact and the lasting effect of the pandemic on PT. This helps to identify patterns for each mode and adapt PT offerings given this information.

Daily data points, concatenated in week vectors, give insights on behaviors and rhythm associated with both PT and COVID-19: results shows that COVID-19 shock intra-week intensity follows a different trend during curfews than the rest of the studied period. These behaviors can be a consequence of working from home, which has been largely encouraged by the French government during curfews. As identified by Cats and Ferranti (2022), this type of analysis can be used to identify new market segments. Special fares could be implemented during specific periods (e.g., curfews) to fit the government's public health recommendations.

Recovery and Stability analysis as defined in this paper use an aggregated indicator, which is the growth factor. The simplicity of growth factor allows for the further analysis of the spatial component and the appraisal of recovery at the stop level. Stops have been compared not only between years (2020 and 2021), but also according to spatial attributes (central, west, east, and transfer; or line belonging). Findings complement the results obtained on intensity, allowing to spatially adapt PT offerings. Thus, specific locations can be identified for further study, aiming to locally modify PT offerings (possibly leading to remove an entire stop or to invest in upgrading the infrastructure at a stop if the pattern seems persistent). Likewise, in context of crisis and constrained resources, temporary offerings adaptation can be made, focusing on peripheral areas' mobility patterns rather than central zones, for which a disuse of the PT system is observed.

Concepts of intensity, recovery, and stability have been assessed through simple indicators, which can be easily implemented for the evaluation of COVID-19 impact on transport systems, at a disaggregated level. To go further, comparative analyses could be conducted by inferring our results with other indicators. Ponte et al. (2018) used the Gini coefficient to measure the heterogeneity of time distribution applied to traffic movement using PT data. (Galeazzi et al., 2021) also used the Gini coefficient as an indicator of spatial heterogeneity for node contribution of PT networks. The outcomes of this research can be implemented in models that need a characterization of stops regarding their ability to endure a shock. For instance, it can be used to improve the forecasting of transit traffic methods, which have been proven to react badly to the COVID-19 shock and shocks in general (Rodríguez González et al., 2021), in implementing stop resilience or vulnerability in models, as carried out by (Yap & Cats, 2021) to predict disruptions and their delay impacts.

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ORCID

Benjamin Cottreau https://orcid.org/0000-0002-5755-8051
Ouassim Manout https://orcid.org/0000-0002-7688-7934
Louafi Bouzouina https://orcid.org/0000-0001-8975-5124

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