# On the bumpy road to recovery: resilience of public transport ridership during COVID-19 in 15 European cities

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## Abstract

COVID-19 has a dramatic impact on the use of public transport (PT). Most European cities report a decline in PT use during 2020 and 2021. Nevertheless, not all cities report similar decline patterns or comparable resilience paths. We investigate the resilience patterns of PT use during 2020 and 2021 in 15 European cities from 11 different countries using clustering and regression analysis of data originating from Google Mobility Reports, the Oxford Policy Stringency Tracker, and COVID-19 reports. Results highlight the variety of resilience patterns of PT use in these 15 cities. These patterns vary in time and space. PT use in some cities recovered faster and more significantly than in others. Findings also suggest that changes in retail and recreational routines had the highest impact on the resilience of PT use in most cities. Changes in workplace routines are also important, but to a lesser degree. The impact of policy stringency on PT use is significant, but less consistent between the 15 cities.

## 1 Introduction

Human physical interaction and geographical mobility are key factors in the spread of COVID-19. Consequently, shortly after the onset of the pandemic, many countries restricted human interactions and limited the mobility of citizens to control the

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spread of the virus. These restrictions had a significant impact on daily routines, especially in densely populated urban areas. Many cities reported, for instance, an unprecedented decline in public transport (PT) demand that has been sustained during 2020 and 2021 (Google LLC 2022; APTA and TransitApp 2022; UNECE 2022). Nevertheless, PT use data over these two years suggests that different cities report different resilience patterns of PT use (Fig. 1). Among 15 cities from 11 different European Union (EU) countries, there are significant fluctuations over time, with negative and positive outliers, but also with some similarities in resilience patterns. It is therefore crucial to explore and explain these differences and similarities.

Two research questions are addressed in this paper: what are the patterns of PT use resilience in the EU during 2020 and 2021? Why are there differences in the recovery paths of PT use among EU cities? From an academic and operational point of view, it is important to investigate these questions to better understand and improve the resilience of PT systems confronted with shocks similar to COVID-19.

Since the beginning of the pandemic, several studies have been undertaken to assess its impacts on PT use at different spatial levels (Al Zein et al. 2022; Bouzouina et al. 2022; Séjournet et al. 2022; Eisenmann et al. 2021; Jenelius and Cebecauer 2020; Wielechowski et al. 2020; Melo 2022; Rasca et al. 2021; Jiang and Cai 2022). These studies report various findings: decline in PT use in favor of the car, the impact of policy stringency on PT, fear of contamination in PT, and the wide adoption of remote activities, particularly during the first months of the pandemic (Gkiotsalitis and Cats 2021). Nevertheless, research on the resilience of the
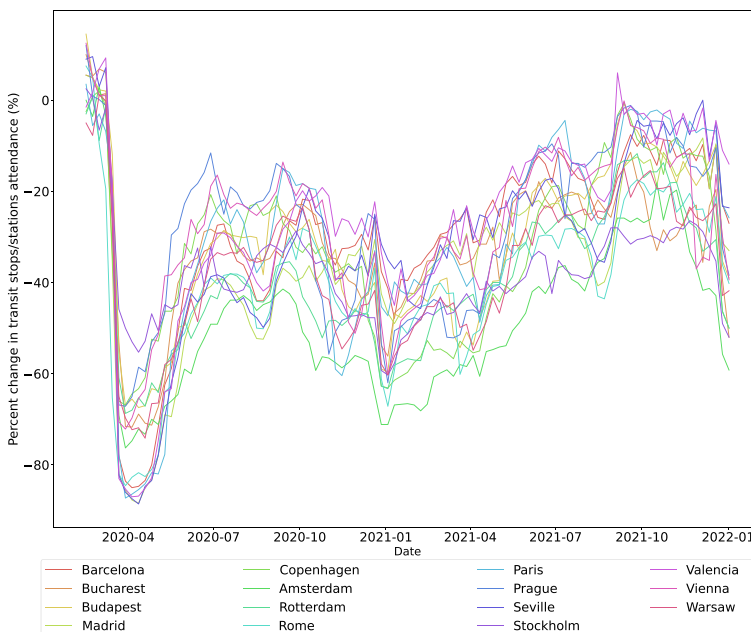


**Fig. 1** Percent change of presence in PT places in 2020 and 2021 according to Google Mobility reports (Google LLC 2022)

PT system during COVID-19 and its enabling recovery factors is still scarce (Sunio et al. 2022; Hsieh and Hsia 2022; Laroche 2022; Vickerman 2021; Xiao et al. 2022; Wang et al. 2022; Zhou et al. 2021). Some studies emphasize the role of government and financial support and the type of contracting in PT resilience (Laroche 2022; Sunio et al. 2022; Vickerman 2021). Others stress the role of anti-pandemic measures (Hsieh and Hsia 2022; Zhou et al. 2021). Some authors emphasize also the heterogeneity in the resilience of PT use among different population profiles (Wang et al. 2022; Xiao et al. 2022). However, most authors focus on specific PT systems, across a particular country, region, or city and during short periods of time, often a few months.

Our research distinguishes itself from previous studies in 3 respects: (i) it performs an international comparison between 15 of the most populated cities in the EU; (ii) it investigates PT use resilience towards COVID-19 during two years: 2020 and 2021; (iii) it uses data with high spatial and time resolutions.

The paper is organized as follows. After an exposition of the theoretical framework (Sect. 2), we describe our data and the analysis methods used (Sect. 3). Next, Sect. 4 offers empirical findings and interpretations, while Sect. 5 concludes.

## 2 Theoretical framework

The resilience of a system refers to its ability/capacity to recover from an endogenous or exogenous shock. There is an extensive literature on resilience in various disciplines (ecology, psychology, economics, political science), while a rising number of studies can be found in regional and transportation economics (see for e.g. Pascariu et al. (2023)). In all cases the focus is on the recovery potential of a complex system after a perturbation.This definition applies as is to PT, where recovery means recovering historical ridership before the shock. From an economic point of view, the decline and recovery of PT use are a direct consequence of changes in PT demand and supply. During the first two years of COVID-19, PT use has been impacted by various factors. Three of them were decisive: restrictive health measures, economic downturn, and fear of infection (Fig. 2).
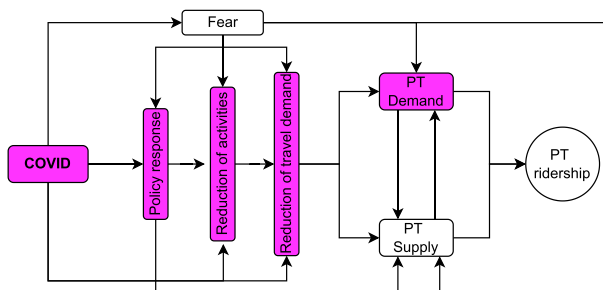


**Fig. 2** Theoretical causal model of the impact of COVID-19 on public transport (PT) ridership. Pink boxes are variables included in this research

To limit the propagation of the virus, strict mitigation measures, like lockdowns, curfews, or travel restrictions, have been introduced in most countries. These measures have induced a significant reduction in out-of-home activities, travel, and PT demand (Wang et al. 2022). The economic downturn, following the onset of the pandemic and the introduction of strict mitigation measures, has caused a reduction in travel needs and PT use as well. Finally, fear of COVID-19, especially in crowded places like PT, has also contributed to a decline in PT demand by either deterring the need for travel or redirecting it to other individual travel modes, like the car or the bike.

The pandemic has also impacted the supply of PT services. In many places, PT supply has been purposefully reduced to discourage mobility and virus propagation (Hale et al. 2021). In other cases, PT supply has been reduced as a consequence of the decline in PT demand, revenues, and shortages in the workforce due to infections or fear of infection (George 2022).

Altogether, COVID-19 had an unprecedented impact on PT demand and supply that led to a decline in PT ridership in most cities. However, the magnitude of this impact differs among cities and needs further investigation.

## 3 Data and methods

To test the above assumptions, we use data on the change in daily routines during 2020 and 2021: workplace presence, time spent at home, number of visits to retail and recreational amenities, stringency level of COVID-19 measures, and the daily number of COVID-19 cases. These variables are, to some degree, proxies for the core factors depicted in pink in Fig. 2. The other factors could not be tested for lack of appropriate data.

### 3.1 Data

We rely on open-access data from various sources to investigate PT use resilience during 2020 and 2021. Google mobility reports provide daily changes in the number of visits to the workplace, retail/recreation places, home, PT stations, parks, and grocery/pharmacy stores. Google collects this data via mobile phones of users who opted in for location history. Data is anonymized and aggregated [see for an exposition Nijkamp and Kourtit (2022)].

Google mobility data are used as a proxy for the change in out-of-home activities and corresponding mobility. The change of each time series is computed relative to the first 5 weeks of 2020 (Jan. 3 to Feb. 6, 2020). Due to confidentiality reasons, data can be spatially aggregated at the sub-regional, regional, or national level. Data at the sub-regional level are not always available for all EU countries. We limit our investigation to the most populated EU cities covered by this level of resolution. These selection criteria result in 15 cities.

These data are, nonetheless, subject to several limitations. Limited information is given on the collection methodology, data representativeness, quality, and

exhaustiveness. The adoption and use of smartphones and Google products are not uniformly distributed in the population. Furthermore, each place category can include a wide range of places according to the needs and definitions of Google. PT stations, for instance, can include subway stations, bus stops, train stations, taxi stands, or car rental agencies.

Despite these limitations, we choose to use these data. Google data is nearly ubiquitous (available in more than 130 countries) and continuous (nearly 3 years of daily data). We assume that these data can be used as a **proxy** to identify changes in travel and activity routines. Google data is not used to measure the absolute attendance of places like work or home, but only the percent change. The percent change can reduce some of the bias in the data (exhaustiveness, for example) by showing the trend of the change.

The stringency index of COVID-19 measures in the 11 EU countries is provided by the Oxford COVID policy tracker (Hale et al. 2021). This index is not available at the sub-regional level for all countries. We use the national policy stringency index for cities, even if some cities might have enacted local regulations different or complementary to national ones.

Data on the number of daily COVID infections at the NUTS 2 and 3 levels are provided by the COVID-19 EU Regional tracker (Naqvi 2021). We compute the sub-regional infection rate per 100,000 capita for each city.

A descriptive analysis of the data is available in Table 1.

### 3.2 Case studies

The resilience of PT ridership is investigated in 15 of the most populated EU cities: Vienna (Austria), Prague (Czech Republic), Copenhagen (Denmark), Paris (France), Budapest (Hungary), Rome (Italy), Amsterdam and Rotterdam (the Netherlands), Warsaw (Poland), Bucharest (Romania), Madrid, Barcelona, Seville and Valencia (Spain) and Stockholm (Sweden). We refer to these entities as cities, despite their different administrative organizations.

The selection of these cities is based on three criteria: (i) availability of data at the city level, (ii) diversification of countries and contexts, and (iii) selection of most populated cities where PT was likely to be used before COVID-19.

**Table 1** Descriptive analysis of the data. Obs. means the number of observations

| Variable | Obs | Mean | Std | Min | 25% | 50% | 75% | Max |
|---|---|---|---|---|---|---|---|---|
| PT | 9283 | −34 | 19 | −94 | −46 | −33 | −21 | 38 |
| Workplace | 9283 | −31 | 20 | −92 | −43 | −31 | −15 | 46 |
| Retail/recreation | 9283 | −33 | 22 | −97 | −45 | −28 | −16 | 21 |
| Home | 9283 | 8 | 8 | −13 | 3 | 7 | 12 | 47 |
| Grocery/Pharmacy | 9283 | −8 | 18 | −95 | −16 | −7 | 3 | 113 |
| Stringency Index | 9283 | 59 | 16 | 0 | 48 | 62 | 71 | 94 |
| Infection rate (per 100,000) | 9283 | 25 | 39 | 0 | 3 | 13 | 31 | 684 |

### 3.3 Methods

To investigate the resilience of PT ridership among the 15 cities, two approaches are used: exploratory and explanatory. The exploratory approach aims to identify patterns of PT ridership resilience. For this, we rely on cluster analysis using a combination of K-means and hierarchical clustering (Hastie et al. 2009).

The explanatory analysis aims at explaining the variability in the decline and recovery of PT use in the 15 cities using regression analysis and explanatory factors from Fig. 2.

#### 3.3.1 Exploratory analysis

To identify PT use patterns, the percentage change (%pc) in PT station visits is divided into weeks of 7 days. For each day, we report the observed %pc. On the basis of this 7-day vector, the K-means algorithm groups observations of different cities using the Euclidean distance as a measure of similarity. The final number of clusters $K$ is chosen using the Silhouette method (see for details Hastie et al. (2009)). The outcomes of the K-means clustering are grouped using hierarchical clustering (HC). The exploratory approach is performed for each year, separately.

#### 3.3.2 Explanatory analysis

A linear regression model is used to explain the variability in the resilience of PT ridership:

$$Y_{t,year,city} = \alpha_{year,city} + \beta_{year,city} \times X_{t,year,city} + \epsilon_{t,year,city} \tag{1}$$

$Y_{t,year,city}$ is the %pc of PT use of a city during a year and a day $t$. $X$ is the vector of explanatory variables. $\alpha_{year,city}$ is the intercept. $\beta_{year,city}$ is the vector of estimated coefficients. $\epsilon_{t,year,city}$ is the vector of errors.

Estimated coefficients can be compared in space and time. These can be compared between cities: $\alpha_{year,city_i}$, $\beta_{year,city_j}$. For the same city, parameters can be compared over time: $\alpha_{year_i,city}$, $\beta_{year_j,city}$. All variables, except the infection rate, are normalized and their magnitude can be compared.

Only explanatory factors that have changed during 2020 and 2021 are included in the regression. Constant explanatory factors, like PT price, are not included since they cannot explain the change in PT use.

## 4 Results and discussion

### 4.1 Exploratory analysis

During 2020 and 2021, the impact of COVID-19 on PT use in the 15 cities can be grouped into 4 different clusters (Fig. 3a, b). Depending on the magnitude of
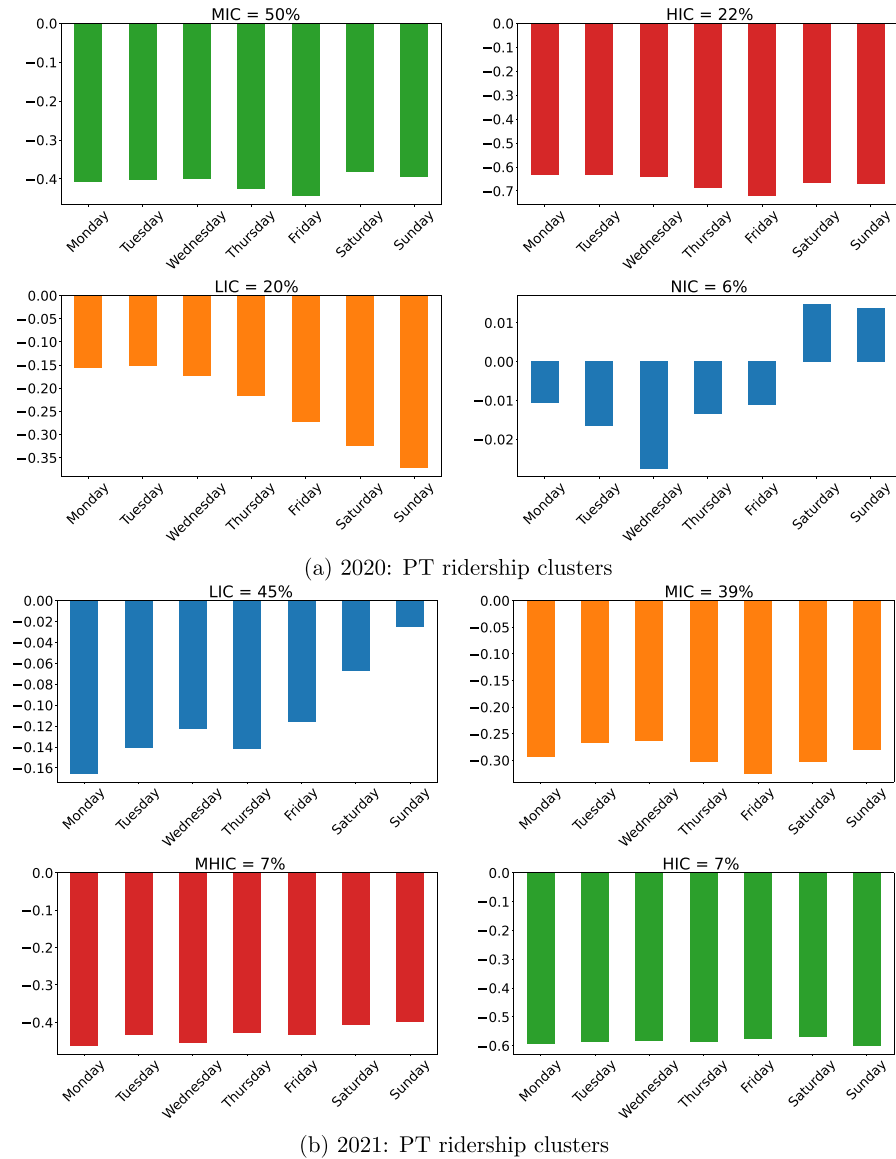
(a) 2020: PT ridership clusters



(b) 2021: PT ridership clusters

**Fig. 3** PT ridership clusters in 2020 and 2021

the impact, these clusters can be described as having no, low, medium, medium to high, or high impact clusters, called hereafter: NIC, LIC, MIC, MHIC, and HIC, respectively.

### 4.1.1 Description of clusters

**For the 2020 results (Fig. 3a) we find:** 50% of PT use data falls within the medium impact cluster (MIC). This cluster groups weeks and cities where the average drop in PT use is medium (−40%). 22% of PT use data falls within the HIC cluster. This cluster groups weeks and cities where the average drop in PT use is the highest (around −65%). The LIC cluster groups 20% of observations. This cluster is characterized by a low decline in PT use during 2020 and a decreasing trend from Monday (−15%) to Sunday (−35%). Finally, 6% of PT data, grouped in the NIC cluster, shows no impact of COVID-19 on PT use during 2020.

Patterns of the impact of COVID-19 on PT use can be investigated in space and time. During 2020, the NIC cluster is exclusively present during the period from 17/02 to 08/03 that preceded the official declaration of COVID-19 as a global pandemic. It is noteworthy that Rome has only one week within the LIC cluster, whereas other cities have two. This is due to the fact that the first major COVID-19 outbreak in Europe (EU) was first officially reported in Italy, hence the earliest impact of COVID-19 on PT use in Italy, and Rome in particular.

The HIC cluster is predominant from 16/03 to 17/05 and during the last two weeks of December 2020. During these periods, most EU countries faced and feared major outbreaks of COVID-19 and took very strict measures to control the spread of the virus, including lockdowns. Noteworthy is the predominance of this cluster in Amsterdam where more than 25 weeks of 2020 belong to this cluster, whereas, in other cities, less than 10 weeks of data belong to the HIC cluster (Fig. 4a). Contrary to Amsterdam, Stockholm has the lowest share of the HIC cluster, meaning that PT use in Stockholm was less impacted by COVID-19 during 2020 than in Amsterdam. This difference can be explained by the singular Swedish policy response to COVID-19 that relied more on citizen trust and responsibility than bans and restrictions.
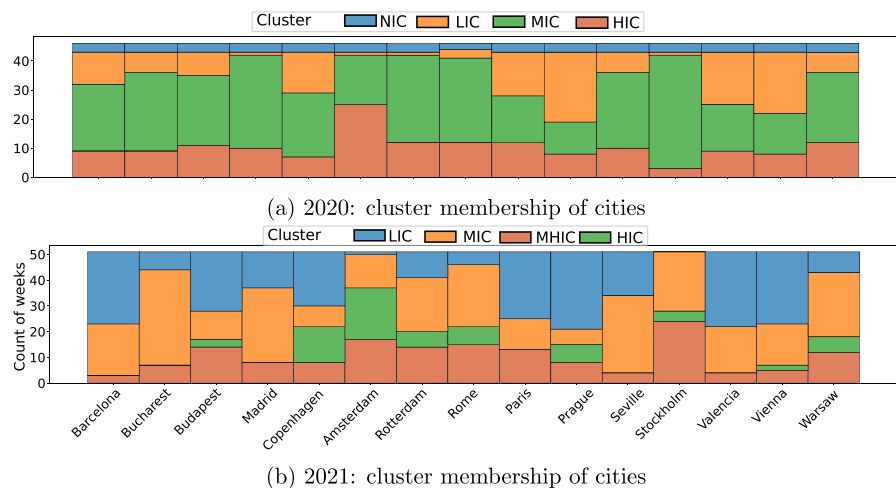


(a) 2020: cluster membership of cities

(b) 2021: cluster membership of cities

**Fig. 4** Cluster membership of cities in 2020 and 2021

The LIC cluster is predominant during the second week of March 2020 and from 07/09 to 14/10. This cluster is characteristic of cities like Prague (24 weeks) or Vienna (21 weeks) (Fig. 4a). The MIC cluster is predominant between 21/05 and 6/09 and between 12/10 and 20/12. It is characteristic of Stockholm (39 weeks), Madrid, (32 weeks) and Rotterdam (30 weeks) (Fig. 4a).

**The 2021 results (Fig. 3b) are as follows:** PT resilience patterns can also be grouped in 4 clusters. The LIC cluster groups observations with the lowest decline in PT use during 2021 (average drop of −11%). This cluster is also characterized by an almost recovery of PT demand during weekends, and a relative increase in PT use during Wednesdays (−15%) and Fridays (−13%) due to an increase in workplace presence during these two days relative to the rest of the workdays. 39% of observations fall within the MIC cluster where the decrease in PT use is medium (−30%), but higher during Mondays, Thursdays, and Fridays due to an increase in remote work during these days. The MHIC cluster groups 7% of data and it is characterized by a medium to high drop in PT use (−42%). The HIC cluster has 7% of observations with a very high impact of COVID-19 on PT use.

The HIC and MHIC clusters are predominant during the first 4 months of 2021 and nearly absent during the rest of 2021. These clusters are especially predominant in Amsterdam (37 weeks) and Stockholm (28 weeks) where PT use has been hardly impacted in 2021 (Fig. 4b). Contrary to these two cities, Spanish cities (Barcelona, Madrid, Seville, and Valencia) are characterized by the absence of the HIC cluster and by having the lowest share of the MHIC cluster. The LIC cluster is predominant between 30/08 and 19/12. This cluster is characteristic of cities like Barcelona, Budapest, Copenhagen, Paris, Prague, Valencia, or Vienna.

### 4.1.2 City clusters

On the basis of the membership of cities to clusters (Fig. 4a, b), we perform a hierarchical clustering (Hastie et al. 2009) to group cities within groups that maximize their intra-group similarity and inter-group dissimilarity. Similarity/dissimilarity is measured using cluster memberships of cities. In 2020 and 2021, 4 distinct city groups can be identified: orange, green, blue, and red (Fig. 5a, b).

In 2020, the city of Amsterdam is isolated in a distinctive group (blue) translating the singular impact COVID-19 had on its PT system with an average decline in ridership of −52% (Fig. 5a). The red group with Stockholm, Rome, Madrid, and Rotterdam, is characterized by a medium to high decline in PT use (−44%). The green group reports a medium decline in PT use during 2020 (−39%). Finally, the orange group is very dissimilar/distant from the rest of the cities. This group reports the lowest decline in PT use (−34%) in 2020. It is noticeable that cities within the same country do not necessarily belong to the same cluster (Dutch and Spanish cities).

In 2021, the city of Amsterdam is, once again, isolated in a group that reports the highest decline in PT use (−44%) and a marginal recovery in comparison to 2020 (Fig. 5b). The green group of Rome, Rotterdam, Stockholm, and Warsaw reports a medium to high drop in PT use (−35%). The red group with Copenhagen and Prague is characterized by a partial recovery in PT use (−27%). Finally, cities in the orange cluster display a noticeable recovery in PT use in 2021 (−23%). In comparison with

(a) 2020: HC of cities
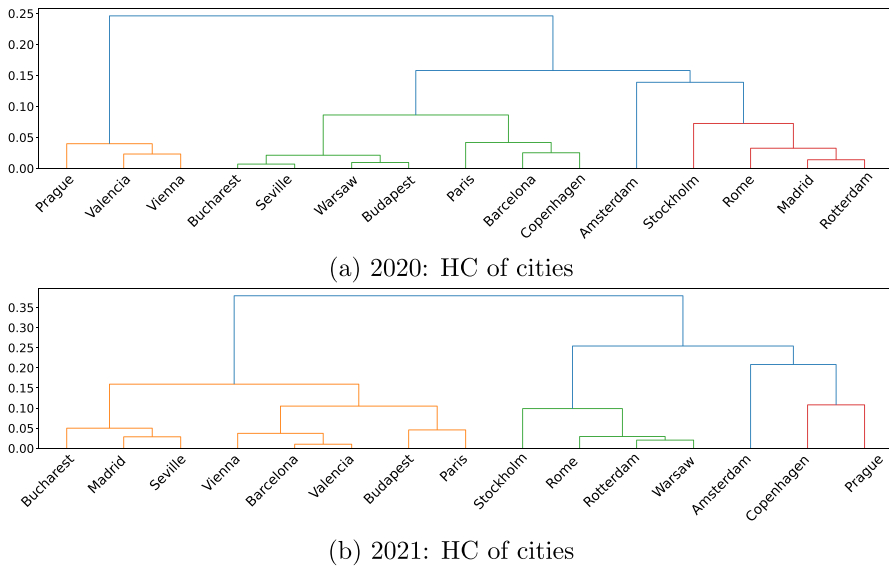


(b) 2021: HC of cities

**Fig. 5** Hierarchical clustering (HC) of cities in 2020 and 2021

the orange cluster of 2020 which includes 3 cities, the 2021 cluster includes 8 cities, 4 of which are Spanish.

Findings of the exploratory analysis are twofold: (1) the impact of COVID-19 on PT use differs among cities, with some cities bearing more similarities than others; (2) this impact also differs between weeks, months and years, with a general recovery trend as time goes by. These results suggest that the recovery in PT ridership is on the way for some cities and a long way off for others. Findings also show that some cities (Spanish cities, for example) report a faster and more noticeable recovery in PT use than others (Dutch cities, for example). Various factors might explain this space-time variability. The next section explores the effect of some of these factors using regression analysis.

## 4.2 Explanatory analysis

After testing several model specifications, the best model includes 3 variables to explain the impact of COVID-19 on PT use in the 15 cities: the %pc in workplace visits, the %pc in retail and recreation visits (Google LLC 2022), and the COVID-19 stringency index (Hale et al. 2021). These variables are significantly correlated (higher than 0.74) with the change in PT use and exhibit acceptable multicollinearity with a Variance Inflation Factor or *VIF* less than 3.3 (Rogerson 2019). A linear specification with intercept is assumed (Eq. 1).

The regression results confirm our assumptions. A decline in the presence in the workplace and in visits to retail and recreation amenities induces a decline in PT use. Conversely, an increase in the stringency of COVID-19 measures causes

a drop in PT ridership. For all cities and for both years, the *Workplace* and *Retail/ Recreation* variables have a significant positive effect ($p < 0.00$), and the *Policy stringency* has a significant negative effect ($p < 0.00$) (Fig. 6a, b).

**The findings for the year 2020 are:** in almost all cities, the change in the use of PT during 2020 depends more on the number of visits to retail and recreational amenities, than on the presence in the workplace or the stringency of COVID-19 measures (Fig. 6a). In 2020, the average effect of the change in retail/ recreation routines was 0.51 in the 15 EU cities. This conclusion does not apply
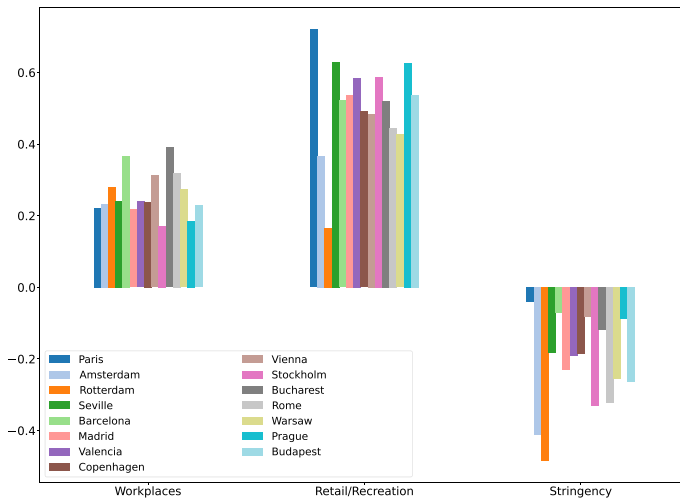


(a) 2020: regression results for the 15 cities
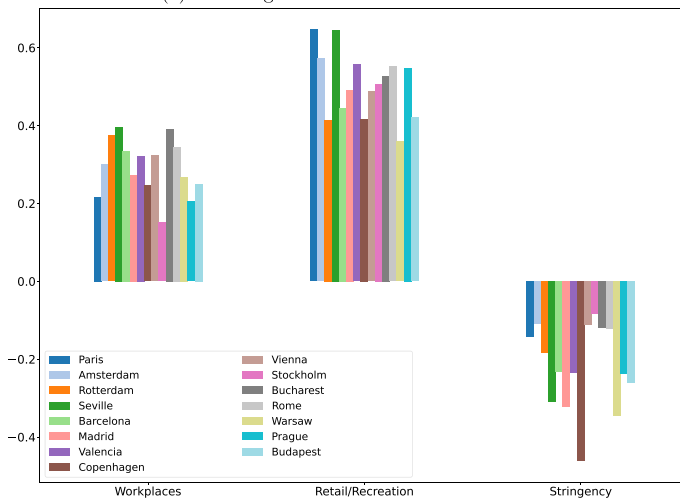


(b) 2021: regression results for the 15 cities

**Fig. 6** Regression results for the 15 cities in 2020 and 2021

to Amsterdam and Rotterdam where PT use is more dependent on policy stringency than on other factors.

In Paris, for example, the change in the number of visits to retail/recreational places has the highest effect on PT use in 2020 (estimated coefficient of 0.72). This means that a 10% drop in retail/recreation visits induces a 7.2% drop in PT use. In comparison, the effects of the *Workplace* and *Stringency* factors are 0.24 and −0.04, respectively. Conversely, in Amsterdam, the *Stringency* factor has the highest effect (−0.41) during 2020, followed by *Retail/Recreation* (0.37) and *Workplace* (0.23) factors.

The *Workplace* factor has its highest effect in Bucharest and its lowest in Stockholm (Fig. 6a). This means that PT use in Bucharest has been more impacted by the change in work routines than in Stockholm. Sweden had, already, one of the highest rates of remote work before COVID-19 as opposed to Romania (Ballario 2020). This can explain the higher resilience of PT use towards disruptions in work routines in Stockholm than in Bucharest.

The effect of the *Retail/Recreation* factor is the highest in Paris (0.72) and the lowest in Rotterdam (0.17). This suggests that the change in retail and recreational habits had a higher impact on the use of PT in Paris than in Rotterdam. This finding can be explained by travel demand generation in both cities. In Paris, nearly 60% of travel demand is due to secondary activities, not related to work or education (Ile-de-France Mobilités 2018).

Despite comparable policy stringency levels (62% in Paris and 56% in Rotterdam), the effect of this factor is the highest in Rotterdam (−0.48) and the lowest in Paris (−0.04). Such a discrepancy can be explained by differences in citizen adherence to COVID-19 measures and the role of local and national cultural and social norms. This discrepancy can also be explained by the definition of the stringency index (Hale et al. 2021) that weighs different policies equally despite their unequal effect on PT use.

**The results for 2021 are as follows:** The specification of Eq. 1 allows the comparison of the coefficients between 2020 and 2021. The effect of the *Stringency* factor on PT use increases between 2020 and 2021 in Barcelona, Copenhagen, Madrid, Paris, Prague, Seville, Valencia, and Warsaw and it decreases in Amsterdam, Rome, Rotterdam, and Stockholm (Fig. 6b). The effect of the *Workplace* factor is stable for most cities and it increases for Dutch and Spanish cities. The effect of the *Retail/Recreation* factor decreases in time for Paris, Copenhagen, Prague, Budapest, Warsaw, and Spanish cities and it significantly increases for Amsterdam, Rome and Rotterdam.

## 5 Conclusion

This research addresses two questions: what are the patterns of PT use resilience in the EU during 2020 and 2021? Why are there differences in the recovery paths of PT use among the EU cities? Findings from 15 EU cities in 11 different countries highlight the variety of resilience patterns of PT use towards COVID-19. These patterns can be summarized in 4 clusters whose distribution in time and

space is not uniform. Similarities and dissimilarities between cities are identified. Some dissimilarities tend to fade away with time, while others seem to persist.

To better explore the factors that can explain this variability, a regression analysis is conducted with a limited number of explanatory variables: change in work, retail/recreational routines, and the stringency of COVID-19 mitigation measures. Findings show that the resilience in PT use during the first two years of the pandemic has been mostly dependent on the change in retail and recreational routines in EU cities. A drop of 10% in out-of-home retail and recreational activities induces an average decline of 5% in PT use. Consequently, the recovery of PT use in the 15 cities, and likely in other metropolitan cities in the EU, will depend on the recovery of retail and recreational activities in the aftermath of COVID-19. It is therefore, important to foresee future trends in retail and recreational activities, especially with the expansion of remote/online activities, like online-shopping, food delivery, grocery delivery, etc.

Findings also suggest that changes in work routines have a consistent effect on PT use in 2020 and 2021. On average, an increase of 10% in remote work induces a drop of 3% in PT use in the 15 EU cities. This result can be of help to explore the future of PT use in the presence of remote work scenarios.

The stringency of COVID-19 intervention has also a significant effect on PT use. In the 15 EU cities, an increase in the policy stringency of 10% induces an average decrease in PT use of 2%. The magnitude of this effect is, however, less consistent among the 15 cities in comparison with the two other factors. When confronted with similar stringency levels, our findings show that PT demand from different countries, and even from cities within the same country, can have different reactions. This finding calls also for a need to customize policy measures and their stringency levels to adapt to local/national contexts.

Clearly, these findings can help academics, PT operators, and decision-makers better understand the impact of COVID-19 on PT use in Europe and help them design, provide and operate resilient PT systems.

This research is subject to several limitations. It relies on data that are proxies for changes in daily routines and not the actual changes in routines. These data are also related to functional units (workplace, retail, PT) that might be loosely defined and not consistently defined in space and time. They also relate to geographical units that are not entirely consistent between the 15 case studies. Regression analysis is also conducted with a limited number of explanatory variables. Other factors that might explain the change in PT use, like PT supply, should also be included if available. Finally, the regression model might be subject to a simultaneity issue. A change in transit demand can also cause a change in daily activity routines. To overcome this issue, we included PT restrictions as an explanatory variable. This variable was statistically not significant and was discarded from the final model.

## Declarations

**Conflict of interest**  The authors have no competing interests to declare that are relevant to the content of this article.

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