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Bike Sharing and Urban Mobility in a Post-Pandemic World

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ABSTRACT The Covid-19 pandemic has abruptly changed well-established mobility patterns, as the need for social distancing and lockdown orders have driven citizens to reduce their movements and avoid crowded mass transit. In this context, we look at the case of New York City's bike sharing system, one of the largest in the world, to gain insights on the socio-economic variables behind urban mobility during a pandemic. We exploit several sources of Smart City data to analyze the relationship between bike sharing, public transport, and other modes of transportation, deriving interesting insights for future urban planning, both city-wide and at the neighborhood level. The New York City case study shows some of the most important trends during the lockdown, and the combination between mobility and socio-economic data can be used to understand the consequences of the pandemic on different communities, as well as the future directions of expansion and management of the bike sharing system and urban infrastructure.

INDEX TERMS Bike sharing, Covid-19, smart city, urban mobility, urban planning.

I. INTRODUCTION

The Covid-19 pandemic that struck the world at the end of 2019 has fundamentally altered social practices and spaces in ways that we still do not fully understand: the current necessity for social distancing might still shape mobility patterns long after the end of the lockdown, and its ripples could have long-term, or even permanent, effects on urban planning and mobility [1]. In the longer term, the effect of climate change and the transition to a low- or zero-carbon economy mean that city planners must shift to sustainable solutions, encouraging both mass transportation and cycling as environmentally friendly and socially equitable alternatives to the use of private cars [2].

However, public transportation can be dangerous during a pandemic, as the virus can easily spread when crowds are in close contact in enclosed spaces such as buses and subways [3]. The recent public transport operator guidelines[1] published by the Union Internationale des Transports Publics (UITP), a Belgium-based international non-profit advocacy organization for public transport, call for a reduction of service as a possible countermeasure. Several cities are then looking at cycling as a healthy [4] and environment- and social distancing-friendly solution [5]: Milan, the major epidemic hotbed in Italy, is currently planning to reconvert 35 km of streets to be more bike-friendly, with 30 km/h speed limits and wide bike lanes,[2] and many other cities are considering similar initiatives.

Even before the Covid-19 pandemic, the growth of bike sharing services from a few small experiments in the 1960s [6] to an almost ubiquitous presence in urbanized environments was altering the shape of urban mobility. Naturally, as bike sharing affects the ridership on public transit and the use of private cars, the pre-existing infrastructure and socio-economic landscape also affects its shape. Bike sharing stations tend to serve richer and more central areas, while providing limited if any coverage to economically disadvantaged neighborhoods [7]: the New York Citi Bike system is heavily skewed towards wealthier areas, although it is currently expanding towards poorer ones such as the Bronx.[3] At the same time, the diffusion of Covid-19 in

The associate editor coordinating the review of this manuscript and approving it for publication was Derek Abbott.

[1]https://www.uitp.org/management-covid-19-guidelines-public-transport-operators

[2]https://www.theguardian.com/world/2020/apr/21/milan-seeks-to-prevent-post-crisis-return-of-traffic-pollution

[3]https://www.citibikenyc.com/blog/major-citi-bike-expansion-map-revealed

New York is strongly correlated with low median incomes [8], ethnic group, and the type of occupation of its residents. Essential workers are exposed to a higher infection risk, and also often have jobs with lower incomes [9], exacerbating socio-economic divisions.

The interplay of bike sharing services and mass transit in urban mobility is another interesting factor, which can greatly expand the potential of both modes of transportation [10]. A survey on transportation mode shifts in Washington DC and Minneapolis (MN) shows an interesting pattern among commuters and leisure riders [11]: while the Washington bike sharing system substantially decreased the use of all other modes of transportation, including buses and light rail, among its users, in Minneapolis a majority of bike sharing users reported a reduced car use, but bus and light rail usage did not significantly decrease, and a large minority actually used mass transit more often, along with walking. The likeliest cause of this trend is the different nature of the mass transit networks of the two cities: while Washington DC has a pervasive metro network with multiple transfer hubs, connecting most destinations within a very short distance, the sparse Minneapolis public transportation network requires users to walk to their destination. Bike sharing can then fulfill this need for a last-mile transportation option. Further evidence for this pattern is given by congestion data analysis [12], which shows that bike sharing systems have a stronger effect on congestion in larger cities, where they can better integrate with mass transit, and at rush hour. To the best of our knowledge, the effect of Covid-19 on the coexistence of bike sharing systems and mass transit is still unknown.

The natural and built environment plays a large role in the use of bike sharing [13] and of cycling as a mode of transportation in general, as does urban and traffic planning: in particular, the creation of bike lanes physically separated from car traffic and the integration of bike sharing with mass transit need to be considered. The presence and design of bike lanes can improve safety and reduce dangerous behavior [14] from cyclists and motorists: Northern European countries such as the Netherlands and Denmark have seen a sharp decline in cycling injuries and deaths thanks to their cycling-friendly urban planning and traffic laws. The experience from these countries [15] shows that urban design plays a key role in encouraging cycling as a mode of transportation, not just bike sharing use. In particular, the perceived comfort and safety of sharing the road with cars affects the gender gap in cycling behavior [16], as women feel generally less safe than men: the introduction of physically separated bike lanes can significantly decrease this gap. North America is currently lagging behind Europe in this regard, although cities like Portland have started implementing cycling-friendly policies and have seen significant increases in bike commuting [17]. Age also plays a role in bike sharing usage: older Millennials in their thirties [18] make up a disproportionate amount of total rides, while Boomers born before 1964 make far fewer trips per person. This is intuitively plausible, as older people might not be as fit, but the combined effects of employment, environmental consciousness, and economical means are complex and need to be studied further.

Disparities between neighborhoods and income groups are not limited to bike sharing service availability, particularly during this pandemic: analyses of mobility patterns through mobile phone records show that richer Americans tend to work at jobs better suited to social distancing [9], resulting in a sharper drop in commuting, while jobs that involve physical proximity and cannot be performed remotely often have lower wages, increasing the risk of infection of economically disadvantaged neighborhoods [19]. Finally, the available data on the people leaving New York City to avoid the epidemic also parallels these inequalities, as the inhabitants of downtown Manhattan left the city in far greater numbers than citizens of the outer boroughs [20].

The combination of these social trends with the threat of climate change and the effect of the current pandemic will have a crucial importance in defining the shape of the cities of the future. The promise of the Smart City paradigm involved using open data to improve services and help citizens [21], and major cities are now in a position to deliver on it. In this work, we present New York City as a case study, analyzing ridership statistics from the Citi Bike bike sharing system (which can also serve as a proxy for general patterns in cyclist mobility) along with public transport data and other socio-economic factors, highlighting how spatio-temporal graph-based analyses can be used for resilient urban planning with social distancing-compatible mobility. We focus on the month of March 2020, during which the city transitioned from its first confirmed case on March 1 to a full lockdown from March 20 onwards. Our data analysis uses several public datasets in conjunction with the bike sharing data to provide a full picture of mobility patterns: the promise of improving services through the use of Smart City open data is not new [22], but the Covid-19 pandemic is requiring a response on an unprecedented scale,

The rest of this paper is divided as follows: in Sec. II, we present a spatio-temporal analysis of the Citi Bike bike sharing system data, discussing the changes in the mobility patterns of users as the pandemic progressed and comparing the patterns in bike sharing usage with those in other forms of public transport, as well as considering several socio-economic features as explanatory variables. Sec. III and Sec IV exploit the connectivity transition and heat diffusion graph analysis techniques to examine these patterns in depth, operating both at the local and at the system-wide level. Finally, we conclude the paper with a discussion on the significance of these results in Sec. V, making considerations on how data analysis in a Smart City framework can help inform urban planning decisions, as well as on the possible policy consequences of our analysis.[4]

[4]The code for the data analysis we performed is available at URL https://github.com/FrancescoPase/bikesharing

II. SPATIO-TEMPORAL ANALYSIS

In order to analyze the ridership data from the Citi Bike system, we divided the month of March 2020 in 4 weeks. Since mobility patterns during the week are significantly different from the ones in the weekend, we mainly considered weekdays. The working weeks we considered go from March 2 to March 6, from March 9 to March 13, from March 16 to March 20, and from March 23 to March 27. This division neatly fits the timeline of the pandemic in New York City, as it progressed from the first confirmed cases in the first week to partial closures during the second week, then to the shut down of public schools and restaurants in the third week, and finally to the full shutdown and shelter-in-place in the last week. We provide a short timeline of the major events in March:

- On March 1, mayor Bill De Blasio announced the first case of Covid-19 in the city, a health-care worker who had visited Iran in February.[5]
- On March 7th, governor Andrew Cuomo declared a state of emergency, and commuter guidelines asked sick individuals to avoid densely packed public transport.[6]
- On March 11, the City University of New York and State University of New York systems were closed by governor Cuomo, moving all classes online from the following week.[7] The first fatality in the city occurred, an 82-year-old woman from Brooklyn.[8]
- On March 12, governor Cuomo announced a ban on public gatherings of more than 500 people, cutting capacity of smaller events by 50 percent and ordering Broadway theaters to shut down.[9]
- On March 16, all public schools closed down by order of the governor, and bars and restaurants were closed by the mayor the following day.[10]
- On March 20, the PAUSE order effectively imposed a statewide shutdown and shelter-in-place. By this time, there were almost 20 000 confirmed cases in New York City, and the number would reach 60 000 by the end of the month.[11]

Fig. 1 summarizes these events graphically, along with the plot of the confirmed cases and deaths over the month of March, using data from the New York City Department of Health.[12]

A recent study [8] shows that the number of Covid-19 cases, and the fraction of positive tests, can be mostly explained by occupation, and that the statistical impact of commuting habits is limited. This suggests that while wealthier, white collar neighborhoods were able to quarantine themselves effectively, essential workers in close contact with each other and the public were possible vectors for the infection instead. As Fig. 2 shows, the outer boroughs have a much higher prevalence of Covid-19. While most of the highly affected areas in the Bronx and Queens are outside the bike sharing network's coverage, we can see that the prevalence in lower Manhattan and downtown Brooklyn is much lower, while it increases in poorer neighborhoods.

Fig. 3 shows a heat map of the ridership data of the subway (above) and the Citi Bike system (below) in the first week of March, from the publicly available data on the Metropolitan Transportation Authority (MTA)[13] and Citi Bike[14] websites. It is easy to see that, while the subway serves an order of magnitude more users than the bike sharing system, the patterns of activity are similar. Lower Manhattan and downtown Brooklyn see the highest activity, while less densely populated areas have less traffic. Traffic follows a bimodal pattern during the day, peaking at rush hour in

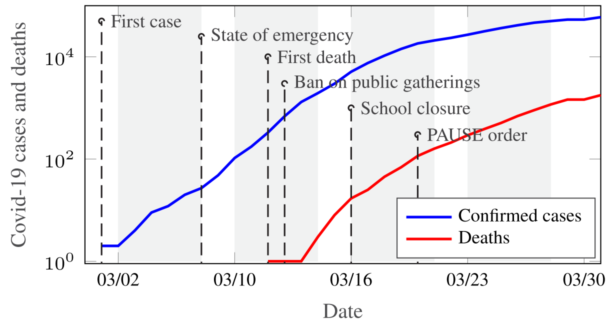


FIGURE 1. Timeline of confirmed cases and deaths on a logarithmic scale, with major events. The shading indicates the weekdays in the four weeks we consider.

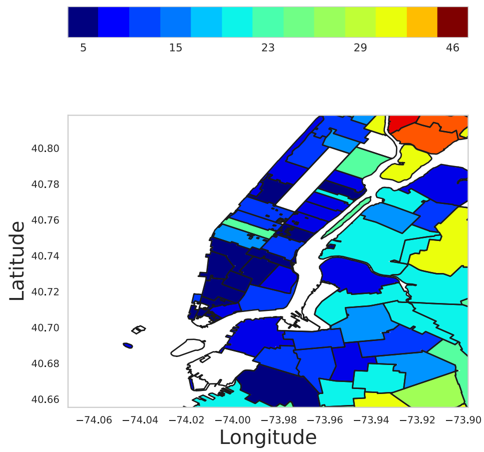


FIGURE 2. Confirmed Covid-19 cases by zip code per 1,000 residents as of June 2, 2020.

[5] https://www.nytimes.com/2020/03/01/nyregion/new-york-coronvirus-confirmed.html
[6] https://www.nytimes.com/2020/03/07/nyregion/coronavirus-new-york-queens.html
[7] https://www.nytimes.com/2020/03/11/nyregion/coronavirus-new-york-update.html
[8] https://www.nytimes.com/2020/03/14/nyregion/coronavirus-ny.html
[9] https://www.governor.ny.gov/news/during-novel-coronavirus-briefing-governor-cuomo-announces-new-mass-gatherings-regulations
[10] https://www.nytimes.com/2020/03/15/nyregion/new-york-coronavirus.html
[11] https://www.nytimes.com/2020/03/20/us/ny-ca-stay-home-order.html
[12] https://www1.nyc.gov/site/doh/covid/covid-19-data.page
[13] http://web.mta.info/developers/turnstile.html
[14] https://www.citibikenyc.com/system-data

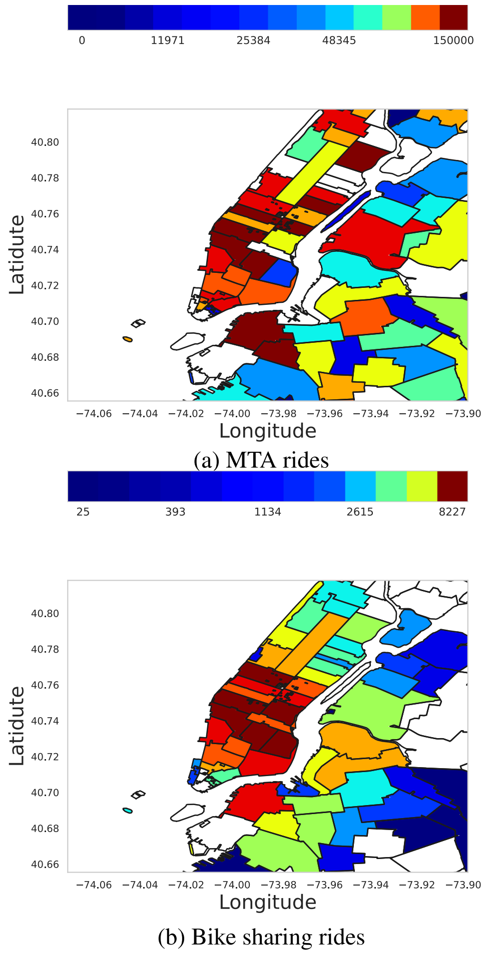


FIGURE 3. Heat map of subway and bike sharing rides during the first week of March. Color values refer to the average number of daily rides.

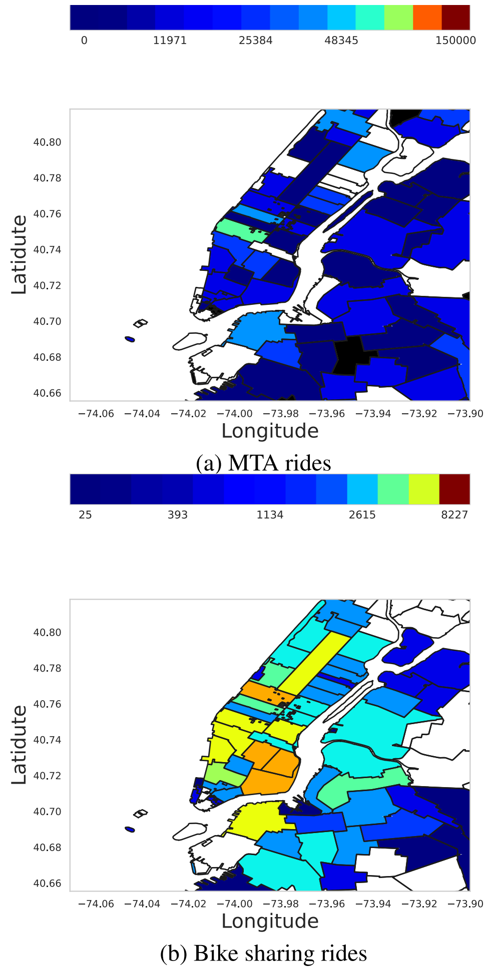


FIGURE 4. Heat map of subway and bike sharing rides during the last week of March. Color values refer to the average number of daily rides.

the morning and the late afternoon. As we will discuss below, both the spatial and temporal patterns were profoundly altered in less than a month by the effects of the Covid-19 pandemic. Interestingly, as Fig. 4 shows, during the last week of March the two systems diverged: while the decrease in the metro rides was uniform across the whole examined area as traffic decreased by almost 90%, the areas with fewer rides in the bike sharing system were less affected, leading to a smaller decrease and a more uniform map.

We first analyze the variation in the number of bike sharing rides: while the general trend shows a reduction of approximately 60% from the first to the last week, the patterns show several interesting features, as shown in Fig. 5. The first noticeable result is that ridership did not decrease from the first to the second week: in fact, it slightly increased, although the effects of bad weather on March 3 and March 6 might account for the difference: the increase in ridership was consistent with what would otherwise be expected based on the increase in temperature. During weekdays, the usage of the system peaks at rush hours in the morning and afternoon, as thousands of commuters use bike sharing to get to and from work. The most significant change happens

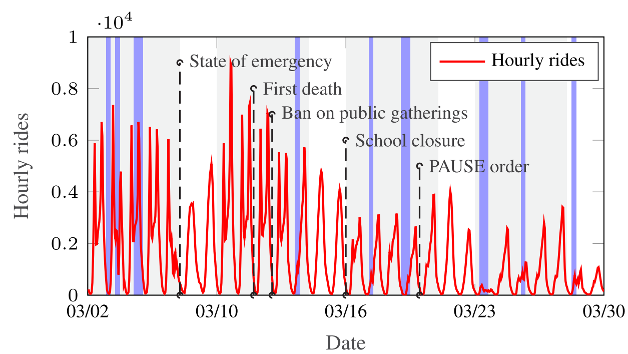


FIGURE 5. Hourly rides between Monday, March 2, and Sunday, March 29. Weekdays are shaded in light gray, while rainy hours are shaded in dark blue.

between the second and third week, coinciding with the period between the ban of public gatherings and the closure of public schools: on average, the number of daily rides decreases approximately by half, and the rush hour peaks are far less prominent, making the hourly patterns more similar to a weekend than a standard weekday. The last week continues this trend, as the peak in the morning almost disappears, while total rides decrease even further. The data from Beijing [23] confirm that this pattern is not limited to New York City, but might be more general in the use of bike sharing systems during the pandemic.

We model the bike sharing system as a graph, with the docking stations as nodes and the rides between them on a given day as edges. We first introduce some basic graph theory definitions and notation. Given a weighted graph G, we define its set of vertices $\mathcal{V}$, the set containing the edges of the graph $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$, and the weighting function $\rho : \mathcal{E} \mapsto \mathbb{R}$, which in our case indicates the number of rides between the two stations. The number of nodes is $V = |\mathcal{V}|$, and the number of edges is $E = |\mathcal{E}|$. We can thus represent missing edges, i.e., the pairs of stations which had no rides between them in the considered period, by assigning them a weight of 0. Let us then introduce the weighted adjacency matrix $\mathbf{W} \in \mathbb{R}^{V \times V}$, where $W_{ij} = \rho_{ij} \geq 0$ indicates the weight associated to the edge connecting nodes i and j. The unweighted degree of a station is defined as the number of other stations it is connected to by at least two trips, i.e., $u_i = \sum_{j=1}^{V} I(\rho_{ij} \geq 2)$, where $I(\cdot)$ is the indicator function, equal to 1 if the condition is true and 0 otherwise. We now define the weighted degree of a node i as $d_i = \sum_{j=1}^{V} \mathbf{W}_{ij}$ and the weighted degree matrix $\mathbf{D} \in \mathbb{R}^{V \times V}$ as the diagonal matrix $\mathbf{D} = diag(d_1, \ldots, d_V)$. As $\mathbf{D}$ is computed on the weighted adjacency matrix, it does not represent the number of connections of each node, but rather the total traffic flowing to and from that node.

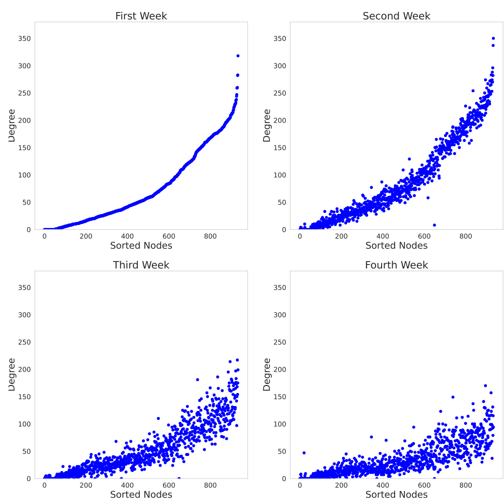


FIGURE 6. **Degree of each station in the four considered weeks, sorted according to their degree in the first week.**

We can then sort all stations by their degree and get the unweighted degree distribution, counting the number of incoming and outgoing edges to and from the stations in increasing order. Changes in this distribution allow us to see how the connectedness of the system changes. Fig. 6 shows the degree of each station in the four weeks, sorted by the value in the first one: this way, we can see not only how connections changed, but also what stations increased or decreased their connectivity. As the figure shows, the degree gradually decreases for most stations, but some stations have a sharper decline: the "hub" stations, which riders use to travel to and from more than 100 other stations, are used less over time. As we will discuss later, these "hub" stations are often placed close to major bus stops and subway and railway stations. Along with the disappearance of the rush hour traffic peaks, this can lead us to the conclusion that most of the traffic on these stations was due to mixed-mode commuting, which was disrupted by the lockdown in the third and fourth week.

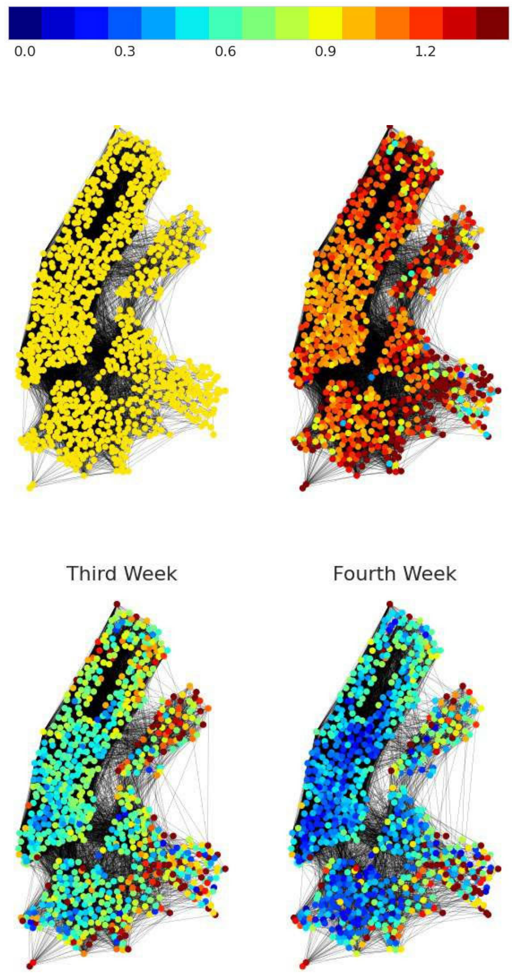


FIGURE 7. **Aggregated weekday degree per station, normalized by the values in the first week.**

Traffic pattern variations have a strong geographical component, as we see in Fig. 7: the "hub" stations we mentioned above are mostly located in downtown Manhattan, and they experience a far sharper decline than those in the outer boroughs. This figure and the following one are normalized by station, i.e., the color of each station is normalized by its degree in the first week, to avoid that the dynamic range of high-traffic stations flattens the variations for lower-traffic ones. For this reason, the value in the first week is 1 for all stations. As the figure shows, stations

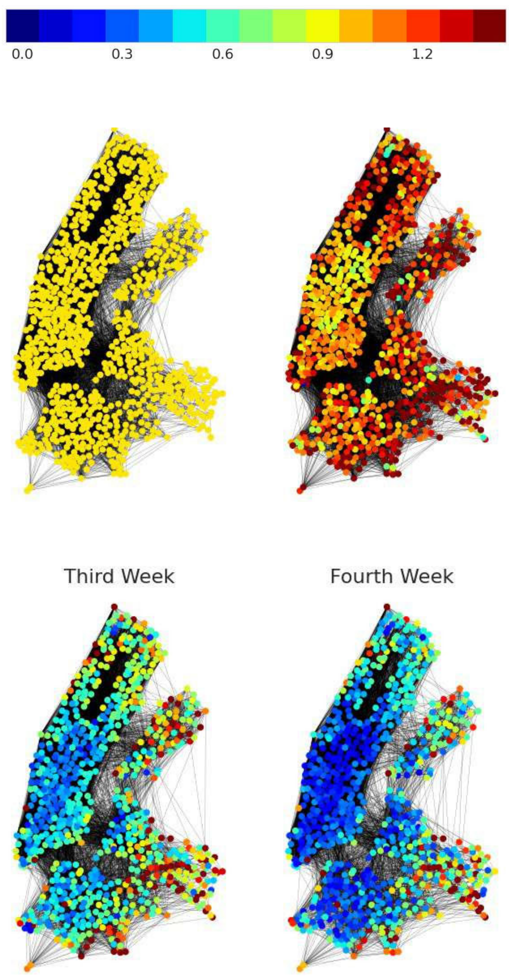


FIGURE 8. **Aggregated weekday traffic per station, normalized by the values in the first week.**

at the edge of the bike sharing system coverage, in the eastern part of Brooklyn and in the Astoria neighborhood, maintain more connections, and sometimes actually increase their degree. The same goes for the total traffic, shown in Fig. 8: while the drop in downtown Manhattan and western Brooklyn is significant, upper Manhattan, Astoria and the rest of Brooklyn see small decreases or even increases in the daily weekday traffic. The socio-economic features of these neighborhoods can partially explain this difference: their inhabitants are often working class, with manual jobs that are ill-suited to remote working. In this case, the bike sharing service can serve an important function, as it enables safe mobility within the city for already disadvantaged categories.

We can also look at the comparison between traffic patterns for the subway and the bike sharing system: Fig. 9 shows the relative subway ridership over the last three weeks of March, mirroring Fig. 8. A glance at the two figures show an important distinction: the decline of subway ridership is much more uniform, affecting the outer boroughs almost as much as downtown Manhattan, while users of the bike sharing system in Astoria and Brooklyn actually increased. As bike sharing

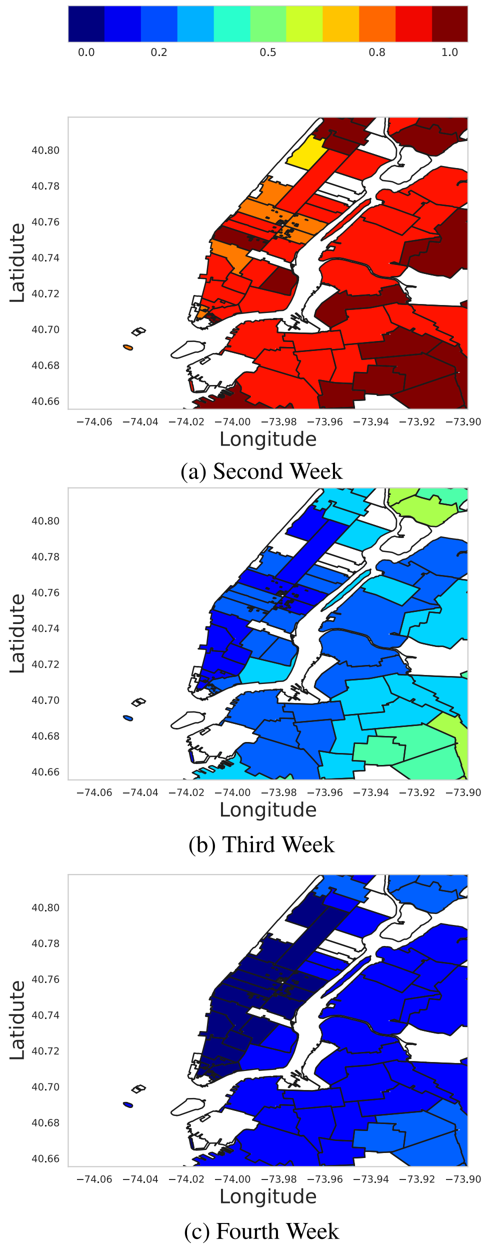


FIGURE 9. **Heatmap of subway traffic by zip code during the same days of previous analysis, relative to the first week.**

rides from these areas also got longer, and several trips were between stations served by a subway line, we can hypothesize that some habitual subway users decided to switch to cycling due to the risk posed by the pandemic. If we assume that cyclists overall follow the Citi Bike system demand patterns, we can conclude that citizens autonomously chose to cycle even without significant incentives, making cycling a fallback option for urban mobility in the pandemic. Naturally, this topic deserves more research, but it should provide further justification for more bike-friendly urban planning: if cycling is encouraged as a safe and healthy alternative, disruption from future epidemic waves can be minimized without

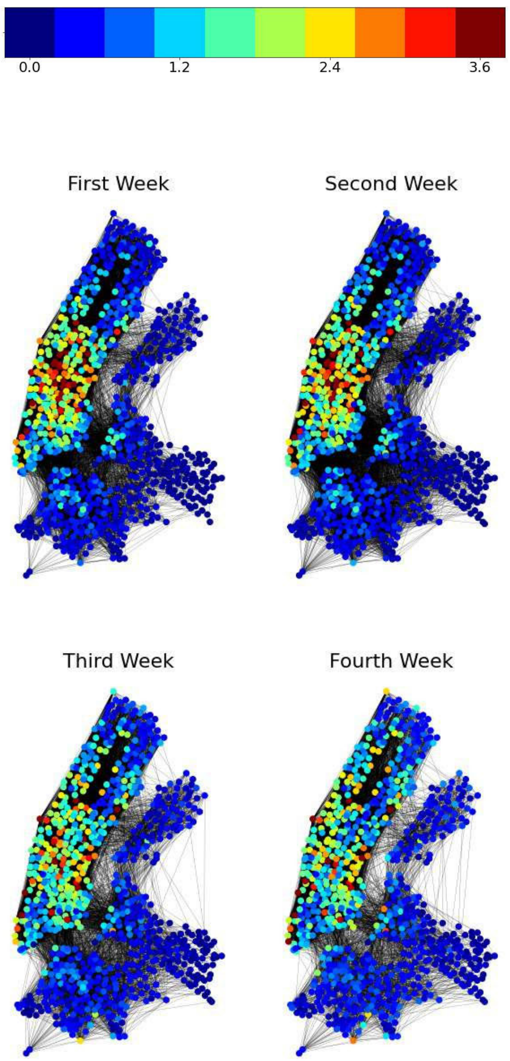


FIGURE 10. **Traffic flows normalized by the average traffic flow per station.**

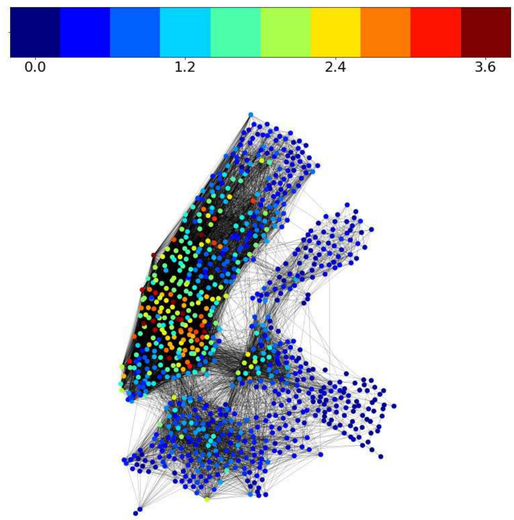


FIGURE 11. **Traffic flows normalized by the average traffic flow per station during the first weekend.**

extraordinary measures. A more comprehensive analysis of the differences in ridership between the subway and the bike sharing system can be found in [24].

Finally, we analyze how traffic shifts in the bike sharing system in each week, looking at the system-wide patterns instead of the station-level variation. Fig. 10 shows the traffic at each station, normalized by the average traffic during each week. We can see that the traffic expands to more stations in upper Manhattan and Brooklyn, but the changes in Astoria and most of Brooklyn that we discussed above are dwarfed by the difference in traffic, i.e., while the traffic in downtown Manhattan decreased sharply and the traffic in the outer boroughs increased, the system is still heavily skewed towards the former. However, it is interesting to note that the red dots in the map for the first week, which correspond to Grand Central Station, Pennsylvania Station and the Union Square subway station, i.e., the busiest mass transit exchanges in Manhattan, disappear in the later weeks. This provides further evidence for the decrease in mixed-mode commuting. As the comparison with Fig. 11 shows, the traffic during the last weeks becomes in some ways similar to weekend traffic in normal conditions, with increased load on riverfront and peripheral stations and a significantly decreased importance of mass transit exchanges. In support of this observation, we performed a simple quantitative comparison between spatial traffic distributions during the weekdays of the first and last weeks, and during the first weekend of March. Let us define with $\mathbf{f}^{k,n} \in \mathbb{R}^V$ the vector containing flow information for each station between the k-th and n-th (included) days of March, where V indicates the number of graph nodes. With this notation, $\mathbf{f}_i^{2,6}$ indicates the aggregate number of trips arriving or departing from station i between the 2nd and the 6th of March. Given the variable number of rides and days considered (weekends contain just two days), we divided the vectors by the average traffic of the considered period over the whole system, obtaining $\bar{\mathbf{f}}^{k,n} = \frac{\mathbf{f}^{k,n}}{\sum_{i=1}^{V} \mathbf{f}_i^{k,n}}$. With this notation, the vectors associated to the weekdays of the first week, the first weekend, and the weekdays of the last week are $\bar{\mathbf{f}}^{2,6}$, $\bar{\mathbf{f}}^{7,8}$, and $\bar{\mathbf{f}}^{23,27}$, respectively. In order to evaluate the traffic "dissimilarity" between two considered periods, denoted with $\mathcal{L}_2(\bar{\mathbf{f}}^{k,n}, \bar{\mathbf{f}}^{k',n'})$, we simply look at the Euclidean norm of the difference vectors, that is $\mathcal{L}_2(\bar{\mathbf{f}}^{k,n}, \bar{\mathbf{f}}^{k',n'}) = \left|\left|\bar{\mathbf{f}}^{k,n} - \bar{\mathbf{f}}^{k',n'}\right|\right|_2$. Smaller values of $\mathcal{L}_2$ reflect a higher similarity between traffic patterns during two different time windows. In our analysis we found $\mathcal{L}_2(\bar{\mathbf{f}}^{2,6}, \bar{\mathbf{f}}^{23,27}) = 20.8$, $\mathcal{L}_2(\bar{\mathbf{f}}^{7,8}, \bar{\mathbf{f}}^{23,27}) = 14.53$, $\mathcal{L}_2(\bar{\mathbf{f}}^{7,8}, \bar{\mathbf{f}}^{2,6}) = 19.28$, which indicates that spatial traffic distribution in the weekdays of the last week is more similar to the first weekend than to the first weekdays. This is confirmed by the fact that the first weekend is more similar to the weekdays of the last than those of the first week of March.

In the last two weeks, many stations close to the city parks see increases in relative traffic, suggesting that leisure trips do not decrease as much as commuting; the main traffic hubs are a previously low-traffic station on the Hudson riverfront, and another one close to the Queensboro Bridge. In general, stations closer to bridges see an increased traffic, giving further proof of the increased inter-borough bike sharing traffic: the station at the Brooklyn foot of the Williamsburg bridge also had especially high ridership. To a lesser extent, so did the Manhattan foot of the Brooklyn Bridge. In normal conditions, only 2-4% of daily trips are across the East River, but this percentage increased to over 5% in the second week of March, and to over 6% in the later weeks. This pattern has remained consistent after the end of March, and the percentage of bridge crossings has reached 9% on one day in late May.

III. CONNECTIVITY ANALYSIS

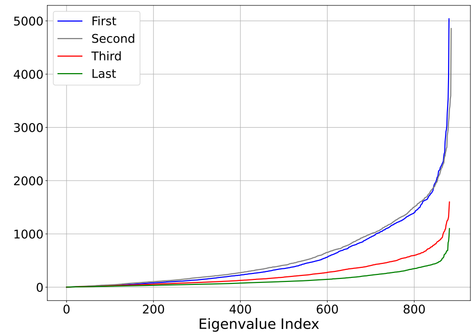
In this section, we analyze the changes in the connectivity of the bike sharing graph, finding regional patterns and examining how they change over the course of the month. Connectivity analysis is a significant research subject in network science, and connectivity-related metrics have already been used for the analysis of transportation systems [25]. Dock-based bike sharing is particularly suited to this approach [26], since the trips are constrained to start and end at the docking stations, which hence represent fixed nodes in the connectivity graph. The use of graph analysis in bike sharing system evaluation and optimization is a growing field of research [27].

The *Combinatorial Laplacian Matrix* $\mathcal{L} = \mathbf{D} - \mathbf{W}$ [28] is an important graph property carrying information on graph topology and connectivity. We can use the eigenvalues of $\mathcal{L}$ to draw some preliminary judgments on the system's behavior. As $\mathcal{L}$ is real, symmetric and positive semidefinite, its eigen-decomposition can be found, and it has non-negative eigenvalues $\lambda_i \geq 0 \quad \forall i \in \{0, \ldots, N-1\}$. If the network is connected, as in our case, the eigenvalue λ_0 is equal to zero, and its associated eigenvector is the constant vector. At this point, it is interesting to observe the spectra of the different graphs in Fig. 12. As we can see, the spectra associated to the first two weeks have larger eigenvalues than the ones for later weeks.

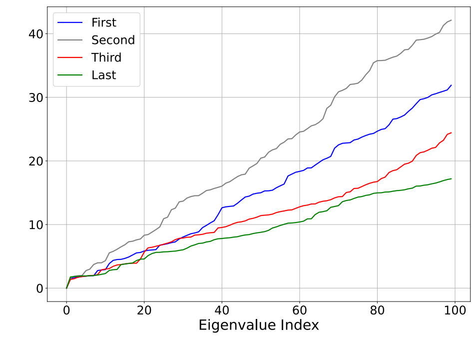
We can also note a small change in the second smallest eigenvalue λ_1, known also as the algebraic connectivity of the graph. This particular quantity has been the subject of intense investigation, as it is generally considered to represent graph connectivity [29]. The first week's graph has $\lambda_1 = 1.57$, while $\lambda_1 = 1.77$ in the last week, suggesting a slight transition towards a more robust network structure [30]. We can spot the same behavior if we look at the Global Clustering Coefficient (GCC), often used in the cluster analysis of bike sharing systems [31], which we define as

$$\alpha(t) = \frac{\text{\# of closed triplets in week t}}{\text{Total \# of triplets in week t}} \quad t \in \{1, 2, 3, 4\}, \quad (1)$$

and indicates the fraction of triplets of nodes which are closed (e.g., they form a 3-clique) within week t graph. Intuitively,



(a) Spectra of the Bike Sharing graphs for the differen weeks of March.



(b) First 100 eigenvalues of the four Laplacians

FIGURE 12. **Spectra of the four different graphs (a); First 100 eigenvalues of the respective spectra (b).**

it can provide a global connectivity measure by looking at how nodes are connected to each other, even if they are far apart in the network. We found $\alpha(1) = 0.0042$, $\alpha(2) = 0.0051$, $\alpha(3) = 0.008$ and $\alpha(4) = 0.0079$. This result is coherent with the intuition on the Laplacian spectra: the graph transitioned towards a better global connectivity, losing local density but preserving longer connections. While λ_1 and the GCC carry global information on the graph structure, we can investigate local connectivity by looking at the Local Clustering Coefficient (LCC) [32]. Given a node i, we define its local clustering coefficient as

$$\gamma_i = \frac{2\left|e_{jk} : j, k \in N_i, e_{jk} \in \mathcal{E}\right|}{k_i(k_i - 1)}, \quad (2)$$

where N_i is the set containing i's neighbors and $k_i = |N_i|$. The LCC basically counts how strongly i's neighbors are connected to each other. In order to have general information on local connectivity, we use the average LCC, denoted as

$$\bar{\gamma}(t) = \frac{1}{V} \sum_{i \in \mathcal{V}} \gamma_i(t) \quad t \in \{1, 2, 3, 4\}, \quad (3)$$

where we have again introduced the time dependency t to indicate the reference week the graph is associated to. Week 1 presents $\bar{\gamma}(1) = 0.418$, in week 2 $\bar{\gamma}(2) = 0.430$, while week 3 has $\bar{\gamma}(3) = 0.311$, and for the last week $\bar{\gamma}(4) = 0.246$. The sharp decline in the third and fourth week reflects the changes due to the Covid-19 mobility restrictions: as we noted in the previous section, the network becomes sparser, i.e., trips to and from neighboring stations with strong connections to each other make up a lower percentage of the overall total.

During the last week of March, the graph is sparser with lower local density and a more balanced structure. This is again due to the fact that longer rides remained active, whereas many shorter paths almost disappeared. Particularly in downtown Manhattan, different "hub" stations present lots of connections (high degree) with many other nodes: usually, these stations correspond to major mass transit exchanges such as Penn Station and Grand Central Station.

We then consider network communities, which should represent crowded New York City areas where people use the bike sharing service to make short trips within a specific region. In particular, we spot several differences in the makeup of the city's communities when transitioning from the first to the last week of March. In order to extract such communities, we adopted the well-known Louvain algorithm [33], which takes into account edge weights and tries to find the partition that maximizes modularity. The algorithm does not use a fixed number of clusters, but finds the best partition in terms of modularity, which we then analyze: the clusters are depicted in Fig. 13. Aside from a few low-traffic stations, the clusters have sharp geographical edges. As we approach the end of March, the changes in the system mobility generate a new community partition. If we analyze the first two weeks, we can notice a clear subdivision of Manhattan into three clusters representing Lower Manhattan (LM) (blue), Midtown Manhattan (MM) (gray) and Upper Manhattan (UM) (yellow). Specifically, if we look at the partition for the first week, we notice that 14th St. defines a rough boundary between the LM and MM clusters, while 42nd St. does likewise between MM and UM. It is interesting to note that *Grand Central Station* (gray) lies exactly along this boundary, thus being an important bridge between the yellow and gray areas. The other two identified clusters define the Astoria (AS) region, grouped together with Williamsburg/Bushwick (WB) (green), and Brooklyn (BR) (red). However, the situation changed during the last two weeks, generating a new division of the Manhattan area. In the third week, the cluster containing the UM region (yellow in the first two weeks, gray in the last two) covers the same area as in the first two weeks, but MM and LM are divided by a North-South axis along the island instead of an East-West one across it as in the first two weeks. The line between the Eastern (yellow) and Western (blue) clusters is along the blocks between 5th and 6th Avenues. Given the lockdown restrictions, user mobility has clearly transitioned towards longer trips along the island on the North-South axis, often along the river front. In the outer boroughs, the algorithm has grouped together WB and BR (red), leaving AS as a separate cluster (green). There are limited changes between the third and fourth weeks: the only major change is that the yellow and blue clusters extend almost to Central Park in the fourth week, indicating that the blocks in MM have a stronger connectivity with LM than with UM.

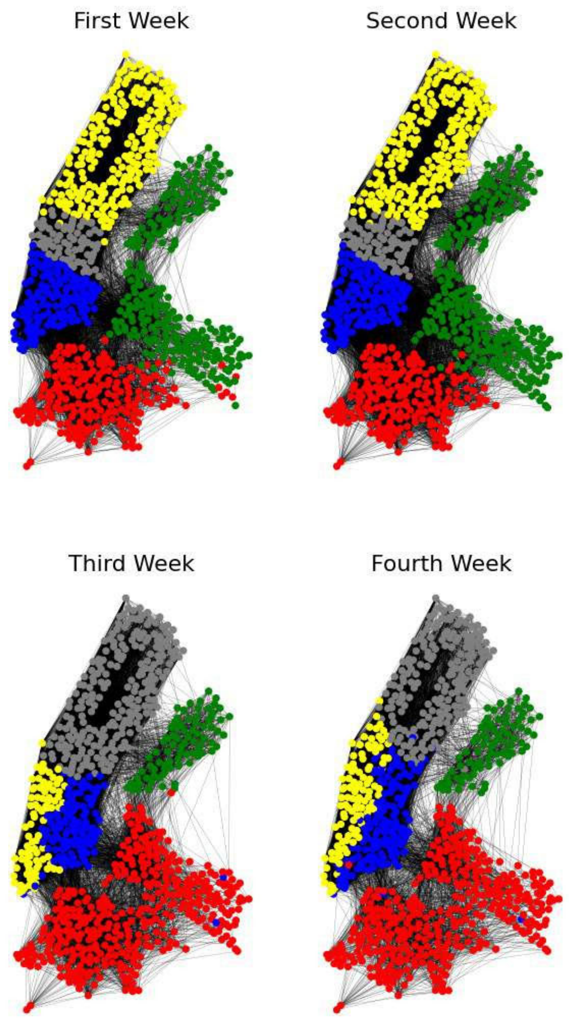


FIGURE 13. Clusters in the weighted graph representing traffic in the Citi Bike network across the four considered weeks.

In order to assess the quality of the partitions, we use a standard metric, the *coverage* [34]. We first define the total sum of weights ρ:

$$\rho = \sum_{(i,j)\in\mathcal{E}} \rho_{ij}. \tag{4}$$

The output of a clustering algorithm is a partition $\mathcal{P}$ of graph vertices such that each set in the partition identifies one community (or class). We can define a cluster function $C : \mathcal{V} \mapsto \mathcal{P}$, such that C_i is the cluster to which node i belongs. In order to assess the quality of the found partitions, we compute their coverage θ, defined as the fraction of the total weight covered by the intra-cluster edges:

$$\theta(\mathcal{P}) = \sum_{(i,j)\in\mathcal{E}} \frac{\rho_{ij}\delta_{C_iC_j}}{\rho}, \tag{5}$$

where δ_{xy} is the Kronecker delta function, i.e., $\delta_{xy} = 1$ if $x = y$ and 0 otherwise. By adopting this metric, it is interesting to see how the previously described transition towards a new graph partition has smoothly occurred. Let's now define $\theta(\mathcal{P}_i)$ as the coverage of the i-th week partitions, we obtain:

$$\theta(\mathcal{P}_1) = 0.713 \quad \theta(\mathcal{P}_2) = 0.683$$
$$\theta(\mathcal{P}_3) = 0.718 \quad \theta(\mathcal{P}_4) = 0.737$$

Although the values are not very different, we can see that between the first and second week, clusters remained qualitatively the same but coverage decreased: as coverage tends to decrease slightly as traffic increases, and the patterns for the first two weeks are similar, this drop can be explained by the slightly higher ridership in week 2. The clustering changes between the second and the third week, as the lockdown goes into full effect: the coverage increases again for the new configuration. In the last week, the clusters still follow the new partition, but the coverage increases again.

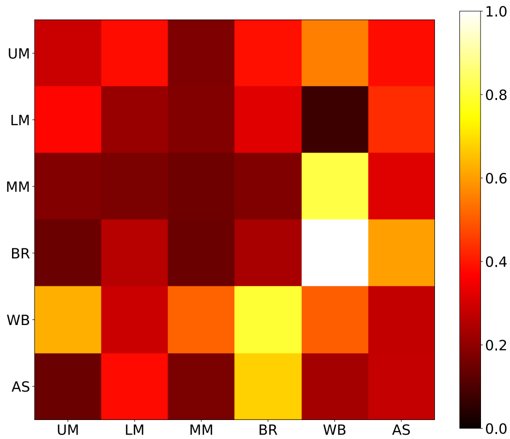


FIGURE 14. Color map representing the first week flow over the last week flow between pairs of NYC areas. The diagonal elements contain internal flows.

To conclude this section, we performed one last analysis. We denote the directed flow (number of rides) between two groups of stations M and N during week t as:

$$\overrightarrow{\rho_{MN}}(t) = \sum_{(i,j)\in M\times N} \overrightarrow{\rho_{ij}}(t), \tag{6}$$

where $\overrightarrow{\rho_{ij}}$ indicates the unidirectional traffic from station i to station j, without considering incoming traffic from j to i. In the directed graph, we can have $\overrightarrow{\rho_{MN}}(t) \neq \overrightarrow{\rho_{NM}}(t)$. We chose 6 geographical areas by taking the 5 clusters identified during week 1 and splitting the cluster containing the AS and WB areas to separate them, thus $\mathcal{P} = \{UM, LM, MM, BR, WB, AS\}$. We then computed each combination of $\overrightarrow{\rho_{MN}}(t)$ $\forall M, N \in \mathcal{P}$ with $t = 1$ and $t = 4$, including intra-cluster flows (i.e., $\rho_{MM}(t)$, which is equivalent to the undirected version). In the end, we computed the ratio between the flows in the first and last week, $\frac{\overrightarrow{\rho_{MN}}(1)}{\overrightarrow{\rho_{MN}}(4)}$, and reported it in Fig. 14. First of all, we can observe that Manhattan is the most affected region, having reduced its rides by an important factor, both within the island and towards the outer boroughs. The only exception is WB, which maintains its connections with UM and MM. Furthermore, the ratio between WB and BR is almost one, whereas flows between AS and WB experience a reduction, but still lower than for Manhattan. These results explain the new clustering in the outer boroughs, as the relatively increased connections between WB and BR cause them to be grouped in a single cluster.

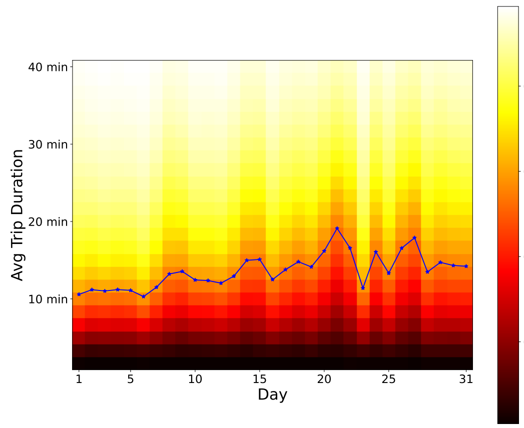


FIGURE 15. Color map representing the empirical CDF of the daily trips duration distribution together with their medians (in blue).

The duration of the trips intuitively matches the results of the previous analyses, which showed a sparser graph with a larger number of long-distance connections: Fig. 15 shows the CDF of trips duration as a color map. Aside from a few variations, which match almost perfectly with rainy days, the average and median trip duration steadily increase: the average grows from about 12 minutes in the first week to almost 20 minutes in the fourth, while the median is lower but also increased from its initial value in the first week. Furthermore, as traffic sharply decreases only in downtown Manhattan, increasing the relative importance of the outer boroughs, this change in the trip duration distribution reflects the change in the usage of the bike sharing system: as short trips downtown become less frequent, longer trips connecting different boroughs make up a larger share of the whole. We also note that the bridges on the East River have experienced increased flows, indicating a stronger inter-borough flow of bike sharing rides.

IV. HEAT DIFFUSION ANALYSIS

In order to track changes in mobility patterns before and after the city-wide lockdown, we exploit graph diffusion processes. As mentioned in the previous section, edges in our graph reflect rides made by bike sharing users throughout the city: thus, the topological structure of the graph lets mobility patterns emerge. The idea behind this analysis is to identify different nodes (i.e., stations) as sources of a diffusion process and see how it evolves over time. In particular, we analyze heat propagation to see how different nodes diffuse heat in their local neighborhoods and use it to characterize users movements around the city, when starting (or arriving) at the source stations. A similar approach was used by Donnat *et al.* [35] to find structural node embeddings for the nodes of general graphs.

To properly define and compute such processes, we draw from the graph signal processing community the tools to analyze and process signals defined over the nodes of a graph [36]. Let us define a signal $\mathbf{f}(t) = (f_1(t), \ldots, f_N(t)) \in \mathbb{R}^N$ as a time-varying vector whose components refer to the nodes of the graph. In our analysis, it represents the "temperature" of a particular node, which will evolve in time according to the well known heat equation that, in turn, accounts for the intensity of traffic between nodes. By exploiting the Laplacian Matrix $\mathcal{L}$, we can define the graph heat process as

$$\frac{\partial \mathbf{f}(t)}{\partial t} = -\mathcal{L}\mathbf{f}(t), \tag{7}$$

which leads to the solution

$$\mathbf{f}(t) = e^{-\mathcal{L}t}\mathbf{f}(0), \tag{8}$$

where $\mathbf{f}(0)$ is the initial condition. In our analysis, we use as initial condition a simple function $\mathbf{f}(0) = C\boldsymbol{\delta}_i$ and $\boldsymbol{\delta}_i$ is the N-dimensional vector with value 1 in the i-th component and zero otherwise. In our analysis, $C = 100$. Eq. 7 represents a dynamical linear system evolving on the graph, thus it can be properly analyzed by looking at its eigenvalues and eigenvectors. In short, at each time instant, the quantity $f_i(t)$, i.e., the value of the signal on node i, is spread among node i's neighbors with an intensity that is linearly proportional to the values of $\mathbf{f}(t)$ on those neighbors and to the weights assigned to the respective edges, i.e., the intensity of traffic between the nodes. In this way, when hub-like nodes are heated at time 0, heat will immediately reach local clusters almost uniformly. The consequence of this is that during the first week, the evolving process gets stuck in well-connected clusters thus taking more time to jump into other parts of the network. On the contrary, during the last week, long-distance routes are almost preserved if not increased, thus making it easier to quickly reach the corners of the network, whereas the local connections within clusters are reduced.

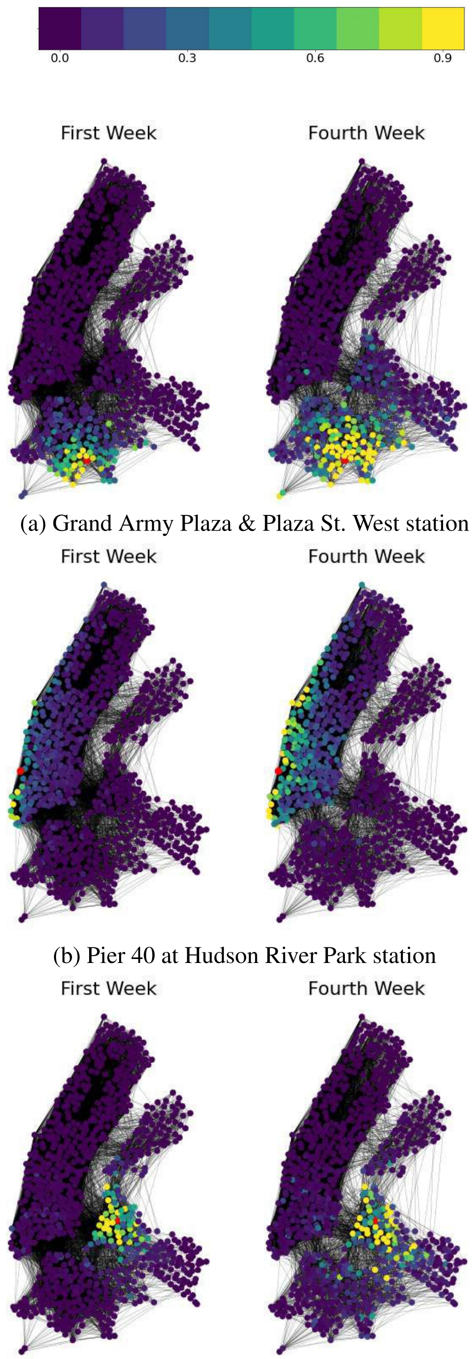
Given the structure, the solution has a simple form and a well defined asymptotic behavior:

$$\mathbf{f}(t) = \mathbf{U}e^{-\Lambda t}\mathbf{U}^T\mathbf{f}(0) \rightarrow \lim_{t\to\infty}\mathbf{f}(t) = \mathbf{u}_0\mathbf{u}_0^T\mathbf{f}(0), \tag{9}$$

where Λ is the diagonal matrix containing the Laplacian eigenvalues, and $\mathbf{U}$ is the matrix containing its eigenvectors, with $\mathbf{u}_0$ being the zero eigenvector (i.e., that associated to the zero eigenvalue). The necessary time to reach the asymptotic solution is hard to compute but is dominated by the first non-zero eigenvalues (the last components to vanish).

Therefore, we analyze how heat diffusion patterns have changed from the first to the last week of March for different source stations. We report here three significant analyses, shown in Fig. 16:

1) **Grand Army Plaza & Plaza St. West**: This station is located in Brooklyn, close to Prospect Park, and



(a) Grand Army Plaza & Plaza St. West station

(b) Pier 40 at Hudson River Park station

(c) N 12th St & Union Ave. station

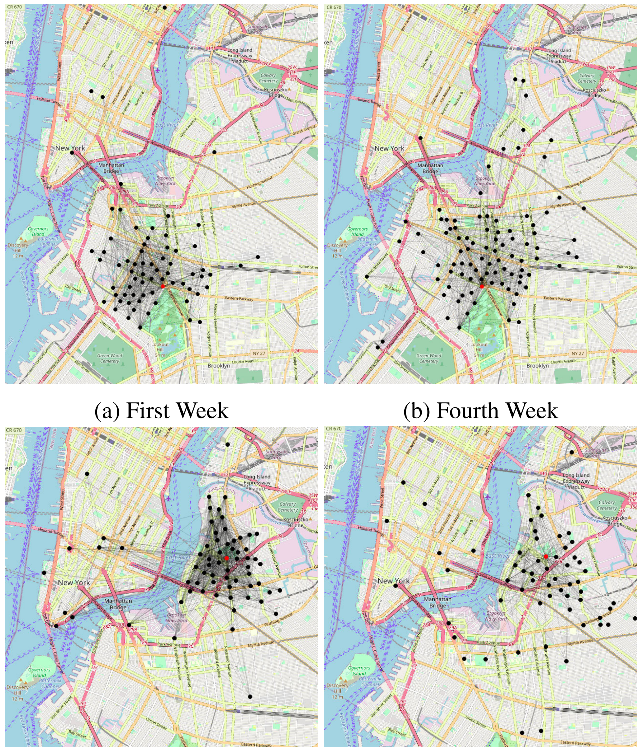
FIGURE 16. Heat Diffusion process starting from three different stations. All snapshots are taken at time $t = 3$ s. Colors of nodes represent their fictitious temperatures, which change as heat propagates through the network.

presents an opposite behavior with respect to the majority of stations. Indeed, its unweighted degree went from 69 to 94, thus being more connected to the rest of the graph during the last week of March. Moreover, its flow increased by $\sim 42\%$, going from 55 to 78 trips per day. It is also possible to observe how the heated area has increased, reaching several nodes in WB and a couple in LM.

2) **Pier 40 at Hudson River Park**: This station in Lower Manhattan experienced a small increase in its unweighted degree (from 144 to 149) and in the number of daily trips (from 168 to 182). While the increase in the activity is small, the diffusion process changes dramatically. In week one, heat is quickly spread almost uniformly, and just concentrates in south Lower Manhattan (around Battery Park). On the other hand, during the last week of March, many nodes maintain a high temperature, and the flow mainly spreads along the banks of the Hudson River. Moreover, if we compute the LCC and denote this particular station as $P40$, we find $\gamma_{P40}(1) = 0.48$ and $\gamma_{P40}(4) = 0.25$, thus indicating that the station's neighborhood becomes sparser than the system as a whole, justifying the new yellow cluster that emerges in Fig. 13.

3) **N 12th St & Union Ave.**: In this particular station, located in Williamsburg next to McCarren Park, traffic flow and unweighted degree both decreased, by $\sim 31\%$ and $\sim 9\%$ respectively. This makes the heat diffusion plot appear counterintuitive, as the area reached by the diffusion algorithm has grown, and heat flow can quickly reach several stations in Manhattan. This can be explained by the fact that, although traffic in general has decreased, and users reach fewer stations overall, the relative importance of longer trips has increased, and while the distribution of trips in the first weeks was heavily skewed towards close stations, it becomes more uniform in the later weeks. Again, we can observe a significant difference in the LCC, decreasing from $\gamma_{N12}(1) = 0.39$ to $\gamma_{N12}(4) = 0.13$, thus making it easier for this node to spread the diffusion to further stations (i.e., longer trips are still maintained).

We remark that the stations chosen here have good connectivity during the whole month and are located in different regions of the considered area. The Brooklyn station's heat diffusion pattern is another hint on how the graph structure has evolved preferring long-distance routes and being less dense in local communities. In the fourth week, it is easier for heat flow to reach further stations with a non-negligible amount of energy not because connections are stronger overall (they decrease by about 67% over the whole graph), but because the origin node has fewer strong connections with close-by nodes, while connections to other stations further away are preserved, and in some cases even get stronger. In other words, while the overall traffic decreases, longer trips are still performed with the same, or even increased, frequency. In order to visualize this, Fig. 17 shows the subgraphs containing the Grand Army Plaza & Plaza St. West and N 12th St. & Union Ave. stations (in red) and their neighbors (in black) during the first and last week of March. Again, this analysis can graphically present similar results, showing the sparser but enlarged topology of the two last week graphs, Fig. 17b and 17d, with respect to the graphs for the first week, Fig. 17a and 17c.



(a) First Week (b) Fourth Week

(c) First Week (d) Fourth Week

FIGURE 17. Subgraph composed by the neighbors of the Grand Army Plaza & Plaza St. West station during the first (a) and fourth (b) week of March. Subgraphs for the N 12th St & Union Ave station in (c) and (d).

V. CONCLUSION: SMART CITIES, BIKE SHARING SYSTEMS, AND URBAN PLANNING

Over the past few years, bike sharing systems have filled an important niche in urban mobility [37], and several studies have focused on the analysis of the data these systems generate, often correlating them with other Smart City applications, to get insights on the citizens' habits and needs and to improve public services. Naturally, determining the best directions for the expansion of the bike sharing system is the first and foremost application of these analyses [38], providing system planners with insights on where new stations and additional capacity would be most needed, but bike sharing data can also help researchers get insights on deeper patterns in urban mobility and society.

The use of bike sharing data in Smart Cities [39] is not in itself a new idea: this kind of analysis has already been performed to assess the impact of bike sharing on public transport in Helsinki [40], and several other works have tried to glean insights about mobility patterns from bike sharing trip data. However, the unprecedented impact of the Covid-19 pandemic and the subsequent lockdown has completely upset the normal flow of citizens and commuters, and the shape of the urban landscape after the reorganization that will inevitably follow the end of the pandemic is still unknown. As commuters avoid mass transit and turn to private cars, the risk of a "carpocalypse" congesting the city's roads and posing a danger to the safety of pedestrians and cyclists is serious [41], and ways to avert it are still under discussion. Although major cities already had strategies for unforeseen events [42], also because of previous epidemics [43], the scale of the Covid-19 pandemic is unprecedented. No single policy intervention is enough to mitigate this risk, and most proposed approaches involve interventions on multiple fronts [44]. These include the protection of transit workers and users by increasing safety measures such as masks and frequent surface disinfection, the encouragement of alternative transportation modes that do not increase traffic [45], such as walking or cycling, the promotion of remote work and the staggering of work hours to reduce the congestion at rush hour [46]. In general, the increased mode share of car travel over short and long distances [47] needs to be counteracted with policies at the societal level, as the necessity of planning urban and long-distance mobility for resilience to future pandemics [48] must always consider the reality of climate change. The extreme fluidity of the situation presents opportunities for a more sustainable urban planning and mass transit organization: as cycling can play a central role in the post-pandemic urban mobility, and its importance as a daily mode of transportation has actually grown during the pandemic due to the disruptions in mass transit schedules, analyzing bike sharing data can give important inputs to this redesigning process.

In this work, we presented an analysis of the bike sharing data during the month of March 2020, observing the changes in New Yorkers' mobility patterns in response to the pandemic and the countermeasures against it. The Citi Bike data largely confirms the overall patterns observed by social scientists, with wealthier neighborhoods in Manhattan being more able to socially distance than poorer areas with a high percentage of essential low-wage workers. We also provided an analysis of the public policies that could shift the mobility of the city towards more sustainable alternatives, and of the complications arising from the pandemic and the risk of future epidemics.

Our analysis of mobility patterns provides evidence that bike sharing, and cycling in general, can provide a flexible and eco-friendly mode of transportation for shorter trips [49] as users are wary to return to mass transit after the pandemic, aiding the unavoidable transition to a greener mobility to tackle the looming issue of climate change. Aside from immediate considerations about the design and expansion of the bike sharing system itself, we can make some broader policy considerations to encourage the growth of cycling as a primary mode of transportation in the urban environment.

Citi Bike's Critical Workers program,[15] which started at the end of March, is a factor that is contributing significantly

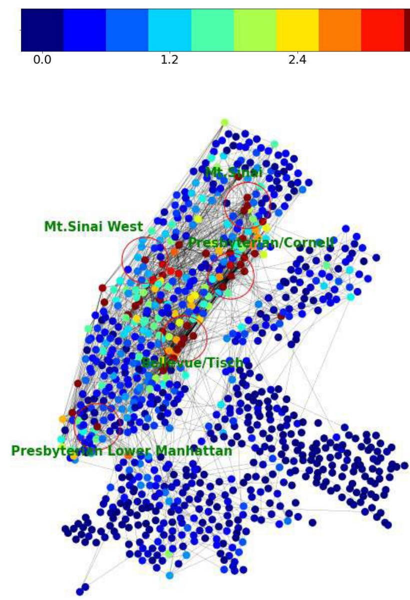


FIGURE 18. Traffic from Critical Workers Program users during the first week of May, normalized by the average station flow.

to the effort towards making cycling more palatable to commuters: 18 000 essential workers got a free subscription to the service, and stations close to hospitals and health care centers have become some of the most utilized ones in the system. Indeed, even though the program has been extended to general essential workforce, Fig. 18 shows that even in May the stations with the highest traffic from users of the program are close to the bigger Manhattan hospitals. The total workforce traffic has increased each month since the program started: while the program accounted for a negligible percentage of the total number of trips over the last few days of March, it made up $\sim$ 4.7%, $\sim$ 7.8% and $\sim$ 8.1% of the total traffic in the months of April, May and June, respectively (data collected until the 23rd of June). It is interesting to notice that, even though the program had barely started in March, Fig. 10 showed an initial flow transition towards those hot stations. These observations, together with those on social distancing and mobility in the outer boroughs, have to be considered in the development of future stations and urban planning in general. Expanding similar programs in the future, and making bike sharing more affordable in general, might be a catalyst to the expansion of the service's importance as a mode of transportation after the pandemic, but urban development needs to move in the same direction: the integration between mass transit and bike sharing might play a significant role in encouraging this trend [50]. Bike sharing has the potential to increase metro stations' catchment area, and survey shows that as many as 10% of total metro rides [51] follow the bike-and-ride paradigm: as the risk of infection decreases, the mass transit system can gradually resume full operation, achieving a greater synergy with the cycling infrastructure and reducing the environmentally damaging reliance on private cars and taxis.

[15]https://gothamist.com/news/citi-bike-promises-to-add-thousands-of-e-bikes-this-summer-as-nyc-reopens

As we discussed in the introduction, bike sharing and cycling in general are strongly dependent on the urban environment: bike lanes can significantly increase bike sharing traffic in an area [52], with the connectedness of the bike lane network also playing a key role, allowing for avoidance of roadway cycling, and increasing the ease of travel between any two points in a city [53]. The use of bike sharing data can also help design new bike lanes, as it can be used as a proxy for cycling-based mobility as a whole [54]. If GPS data is available, wide detours taken by the users to avoid dangerous roads and intersections can be identified, giving important indications for policymakers and traffic planners.

A specific example from New York's Citi Bike is given by the RFK Bridge, connecting northern Manhattan with the Bronx and Queens, which does not have a bike lane, but only a pedestrian path. While the Bronx was not yet served by Citi Bike during March (the first Bronx station was installed on May 7th, and Citi Bike has 36 stations in South Bronx as of June 30, 2020, and growing), part of it can actually link the Astoria neighborhood with the Upper East Side, at the northernmost edge of the service coverage area. As we discussed in Sec. II, cycling traffic between these two areas increased during the Covid-19 pandemic, as did East River crossings in general, but the route between them requires either a long detour or going through pedestrian-only paths. Adding a bike lane to the bridge would provide a direct link between them, further encouraging commuters to cycle and reducing congestion on public transit and road traffic.

Naturally, all the considerations above become more urgent in light of the Covid-19 pandemic: the potential infection risks of crowds and enclosed spaces have resulted in a significant reduction of mass transit ridership, and as citizens return to work the impact of transit users shifting to driving on commuting times will be significant [55]. New York City is responding to the crisis by limiting car traffic over 100 miles of streets through the Open Streets initiative[16] and instituting new bike lanes.[17] While determining the effect of these measures on public health and traffic congestion needs further study, the absence of a second wave in the city during the summer is certainly a positive sign. As we discussed in the introduction, the expansion of the bike sharing service to the outer boroughs[18] is another positive development, mitigating racial and class inequalities in the availability of the service and allowing essential workers access to the system. A comprehensive review of existing policies on sharing systems and the issues facing Smart Cities can be found in [56].

At the moment, bike sharing does not have the capacity to handle all mass transit users [57]: the Citi Bike system has about 15 000 bikes on the streets, and the maximum registered number of daily rides was approximately 90 000, while daily subway rides peaked at just over 6 million in 2014. If cycling and bike sharing are part of the city's plans for post-pandemic urban mobility, the capacity of the system will need to be significantly increased, as well as reach the whole city. Economic considerations also come into play, as the cost of the bike sharing service must be low enough to make it an enticing alternative for commuters. Furthermore, an appropriate bike plan [58] can increase private bicycle use along with Citi Bike ridership, making up for a significant fraction of pre-pandemic subway rides and thus decreasing both the risks for the health of the riders in case of future epidemics and the traffic congestion in the city. Previous studies [59] show that bike sharing can have a catalyst effect on cycling, encouraging the development of infrastructure and cycling in general.

[16]https://www1.nyc.gov/html/dot/html/pedestrians/openstreets.shtml
[17]https://www1.nyc.gov/office-of-the-mayor/news/342-20/mayor-de-blasio-adds-12-more-miles-open-streets-nine-miles-new-temporary-protected-bike
[18]https://www1.nyc.gov/html/dot/html/pr2020/pr20-021.shtml

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