Navigating the Post-Pandemic Urban Landscape: Disparities in Transportation Recovery & Regional Insights from New York City

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ABSTRACT

The onset of the global Covid-19 pandemic in early 2020 brought many transportation systems in North America to a standstill. As life returned to normal, various modes of transportation exhibited differing rates of recovery, with disparities across regions. Limited research has delved into the regional variations in the recovery of these modes of transit over the past years. Such analysis is crucial for gaining insights into urban recovery and resilience, as well as understanding the factors influencing such recovery. In this work, we investigate the usage recovery of taxis, ride-hailing services, and subway ridership following the Covid-19 pandemic. We focus on New York City as our case study, employing clustering techniques to identify neighborhoods with similar recovery patterns. Furthermore, we examine the socio-economic, demographic, and built-environment factors contributing to regional variations in this recovery. Our research findings reveal that different modes of transportation responded differently to the pandemic, and these responses exhibited regional disparities. These findings hold significance for future health-related emergency response strategies and the regulation of existing transportation infrastructure.

1. Introduction

The emergence of the novel SARS-CoV-2 virus in late 2019 lead to the subsequent Covid-19 pandemic which profoundly reshaped our world. Among the myriad of consequences stemming from the pandemic was a profound shift in human mobility and transportation patterns. Both global and local transportation systems underwent substantial changes due to enforced travel restrictions, mandates for remote work, and alterations in individuals' daily routines. Urban transport systems, encompassing subways, buses, taxis, and ride-hailing services, witnessed drastic declines in trip volumes as the public adopted social distancing measures to mitigate the risk of virus transmission (McKenzie and Adams, 2020). In the United States, for instance, ridership across all public transport modes plummeted by an astonishing 73% (EBP US, 2021). In major cities such as New York City (NYC), the repercussions were acutely felt following the implementation of the "New York State on PAUSE" executive order (Cuomo, 2020), a set of policy actions taken to curb the transmission of the virus. At the height of the pandemic, NYC subway ridership experienced a dramatic decline, plummeting to a mere 10% of its usual volume. Simultaneously, the number of operating yellow taxis, for which NYC is famous, witnessed an 81% reduction between January and April 2020 (Harding, 2021).

While a growing body of literature has examined the immediate impact of the Covid-19 pandemic on transportation systems in many cities, limited studies have specifically focused on the longitudinal recovery of transportation systems over the past three years. Even fewer studies have compared recovery of different modes of transportation in different regions within a major city. In May 2023, the World Health Organization declared an end to the global Covid-19 health emergency (World Health Organization, 2023). While this does not mean that health concern over Covid-19 have dissipated, it does provide a bookend to the pandemic and suggests that now is an appropriate time to examine the longer-term impacts of the pandemic on urban transportation. Provided access to over four years of ridership data for yellow taxis (YT), green taxis (GT), ride-hailing services (RHS), and subway trains (ST), we now have the opportunity to examine how each of these systems was impacted by the pandemic and the unique ways in which each of them did, or did not, recover. Furthermore, we are now able to investigate differences in recovery patterns between geographic regions within a major metropolis. While the majority of efforts on transportation recovery have focused on cities as a whole, we know that the characteristics and populations of neighborhoods vary significantly within cities. It is

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therefore important to understand, not only how different modes of transportation have recovered (and are recovering) from the pandemic, but also how these recovery patterns differ spatially.

NYC provides an excellent use-case for such a study as it was, unfortunately, profoundly impacted by the Covid-19 pandemic (Williams, 2021). Additionally, there is a wealth of open and accessible data in NYC across most major transportation modes. Combining these with socioeconomic and demographic data, as well as variables related to the built environment, we are able to generate a holistic representation of NYC transportation for analysis. The findings from this work will contribute to a growing body of literature related to pandemic resilience and recovery. As urban planners, transportation engineers, and public health practitioners look for ways to prepare for future health emergencies, the findings from our work provide evidence as to how different forms of transportation responded over the past four years and which parts of the city saw the fastest and slowest recovery. The importance of each transportation mode to the urban transportation landscape should be re-evaluated, and policy action should be taken to bolster those services that are deemed essential to residents. This work informs further efforts that should be taken to identify how different communities can be better supported through improved infrastructure and transport investments. The value of examining transportation recovery in a major metropolis such as NYC for such a case study is that the results of our analysis may be used to inform and inspire policymakers in other large cities.

With these objectives in mind, we will address the following three research questions (`RQ`) with respect to modes of transportation within NYC.

- `RQ1` *Do patterns of recovery from the Covid-19 pandemic vary between modes of transportation? Furthermore, do these recovery patterns mirror Covid-19 cases and other pandemic indices?* To address this, we analyze ridership patterns for four major modes of transportation, namely subway, yellow taxi, green taxi, and ride-hailing service ridership from 2019 to 2022. We correlate these patterns with health data and a government stringency index.
- `RQ2` *Is there regional variability in the recovery patterns for the different modes of transportation? Furthermore, do the transport recovery patterns cluster spatially, and are these clusters consistent across transportation modes?* To address this, we examine the transport recovery pattern of each mode within each NYC neighborhood. We then run k-means cluster analysis to identify commonalities in the transport recovery patterns[1].
- `RQ3` *Finally, can these regional variations in transportation recovery be explained through the socioeconomic, demographic, and built environment characteristics of neighborhoods?* To address this, we construct a spatial regression model using a variety of explanatory variables and assess the impacts of each variable on our transportation recovery-dependent variables.

The remainder of the manuscript is organized as follows: In Section 2, we provide an overview of existing work on this topic, providing context for this work and the novelty of our contribution. The data used in our analysis is introduced in Section 3 and our methods of analysis are presented in Section 4. The results from our analysis are provided in Section 5. The broader impacts of these results and further discussion on the findings and limitations are presented in Section 6 with final conclusions given in Section 7.

2. Related work

2.1. The impact of Covid-19 on transport usage

Global and local transportation has undergone considerable alterations due to imposed travel restrictions and changes in individuals' daily routines (Tirachini and Cats, 2020a; De Vos, 2020). After the outbreak of Covid-19 , people used less public transport and more private cars (Abdullah et al., 2020), though there is a nuance to the influence of the pandemic on transportation, which varied by phase (Kim and Kwan, 2021; Tirachini and Cats, 2020b). In response to this upheaval, a number of scholars investigated the impact of Covid-19 on various modes of transportation during the outbreak. For instance, Xin et al. (2022) and Wang et al. (2022) analyzed the spatiotemporal distribution patterns of bike-sharing usage during the early stages of the pandemic finding variation usage by region. Similarly, Jiang and Cai (2022) identified the dynamic impact of Covid-19 on subway passenger flow. Fathi-Kazerooni et al. (2020) employed time-series analyses to demonstrate that changes in subway turnstile usage between March and May 2020 correlated with the prevalence of Covid-19 infections. Further research, as explored by Li et al. (2022), examined

[1]Transport recovery pattern: The sequence of all monthly recovery rates for a specific mode of transport, spanning from March 2020 through December 2022, as illustrated in Figure 3.

the spatiotemporal and behavioral variations in taxi travel across the three waves of Covid-19 . They report that, by the end of March 2022, the volume of taxi trips had still languished at levels well below those prior to the pandemic.

The majority of these studies have focused on the pattern changes in a single transportation mode during the pandemic. Most do not contrast the unique impact experienced by different modes of transport. Limited work has compared two systems within a city. For instance, Teixeira and Lopes (2020) examined the size of the impact on bike-sharing systems and subways during the initial stages of the pandemic. Wang and Noland (2021) compared these two modes from the subsequent reopening of economic activity through the end of September 2020, finding that bike-sharing usage nearly returned to normal, while subway ridership was still significantly lower than pre-pandemic levels. Halvorsen et al. (2023) examined the trends in bus and subway ridership in NYC during 2020 and found that Covid-19 had a more negative impact on bus ridership than the subway.

2.2. Determinants of transport ridership changes

Historically, researchers have endeavored to identify determining factors for various types of human mobility, utilizing a variety of data, methods, and explanatory models. Socioeconomic and demographic factors, such as income, age, race, and employment, have been the predominant characteristics of discussion (Taylor et al., 2009) in much of this work. Additionally, factors closely related to transportation, such as car ownership (Boisjoly et al., 2018) and commuting methods (Graehler et al., 2019), are also considered in these analyses. In recent years, there has been a trend towards examining the impacts of the built environment on transportation. The vast majority of these studies focus on land use (Chakraborty and Mishra, 2013; Sung et al., 2014), network structure (Liu et al., 2019), and what are colloquially referred to as the *5D*s, namely density, diversity, design, destination accessibility, and distance to transit (Li et al., 2020; Pan et al., 2017; Qiang et al., 2022). These components are critical to understanding the multifaceted influences on transportation patterns and ridership.

Following the pandemic, researcher groups have begun to utilize similar methodologies applied to different forms of data to explore how the pandemic has changed travel behavior (Hu et al., 2021; Hara and Yamaguchi, 2021). For instance, Qi et al. (2023) found that in the top twenty metropolitan cities in the United States, regions with a higher proportion of impoverished or Latin*x* populations experienced a smaller decrease in public transit ridership, while areas with higher median household incomes, higher employment rates, and a larger proportion of the Asian population experienced the opposite. Additionally, numerous studies have found a similar relationship between income and ethnicity and a decline in regional transport ridership across various cities (Tirachini and Cats, 2020b; Wilbur et al., 2023; Li and Yuan, 2022; Fernández Pozo et al., 2022; Brough et al., 2021). By comparison, Ghaffar et al. (2020) discovered that in Chicago, census tracts with higher household incomes, a greater number of workers carpooling or using public transit to work, and high land-use diversity, experienced a higher demand for ride-hailing services.

Within NYC, Mai et al. (2023) conducted a comparative analysis of the ridership changes of municipal bikeshare and taxis during 2020. They discovered that the ridership of shared bikes rebounded at a faster rate than taxi trips. Additionally, they found that commercial points of interest were positively associated with the reduction of travel demand across a number of regression models. In another comparative study, Bian et al. (2022) examined the impact of Covid-19 on NYC taxis and ride-hailing services, revealing through spatial regression that areas with a higher presence of elderly citizens, school-aged children, and a higher number of walking or public transit commuters, or areas with higher confirmed Covid-19 cases, were more likely to experience reductions in taxi/ride-hailing trips. Conversely, Li and Yuan (2022) found that in Chicago, the number of people using the subway system correlated positively with the number of Covid-19 cases and deaths. Most importantly, COVID-19's disproportionate impact on racial and ethnic minorities in NYC is attributed to structural and historical inequities and social segregation, including racial residential segregation, economic disparities, and social vulnerabilities (Li and Yuan, 2022; McPhearson et al., 2020).

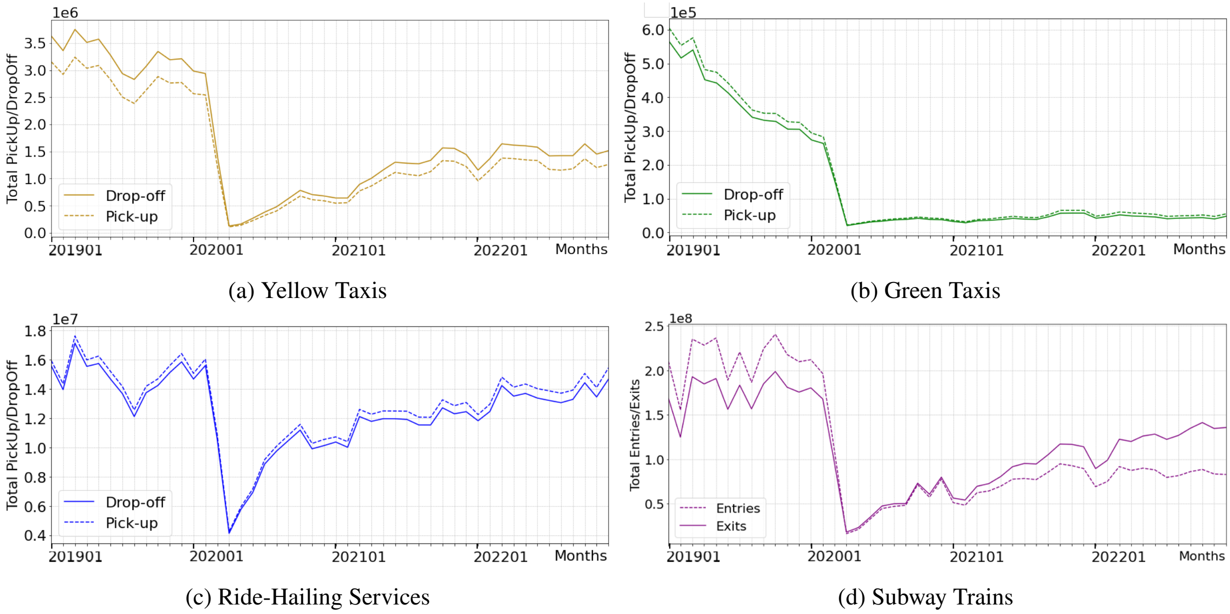
The influence of the built environment has been well examined on Covid-19 ride-sourcing usage (Jin et al., 2023; Debnath et al., 2023). Important work has analyzed its impact on the resilience of public transit systems during the pandemic (Xiao et al., 2022; Yang et al., 2023). Work by Nian et al. (2020) utilized a spatial lag model to explore the changes in the driving forces behind taxi travel in Chongqing, China, subsequently proposing an evaluation model for the social activity recovery level. Furthermore, research by Carrión et al. (2021), used NYC subway ridership and cumulative Covid-19 infection data to measure neighborhood-level disparities, leading to the establishment of a Covid-19 inequity index. Ortiz et al. (2022) developed a multi-hazard risk index by integrating COVID-19 data, urban climate modeling, and social vulnerability indicators, revealing that risk hot spots align with low-income areas experiencing the highest COVID-19 cases and near-surface temperatures.

2.3. Research gap

Despite the prevalence of both descriptive and explanatory research in the early, or single, phases of the pandemic, few studies have focused on longitudinal analyses examining the evolution of Covid-19 over an extended period and measuring travel behavior changes during this time (Lee and Eom, 2023). Such longitudinal studies are instrumental for better understanding the resilience of urban transport systems, human mobility responses to health crises, and equity in access to reliable transportation. To the best of our knowledge, no study to date has compared the recovery patterns of four transport modes across all phases of the pandemic and across regions within a major metropolis.

3. Data

To accomplish our objective of addressing the three research questions we accessed four years' worth of YT, GT, RHS, and ST turnstile data. *Neighborhood Tabulation Areas* (NTA) are used as the geographical units for this analysis. Additionally, Covid-19 cases, socioeconomic and demographic data, point of interest (POI), and built environment variables were explored to better understand the factors driving the changes in mobility patterns. These data were included as independent variables in our spatial regression model.



(a) Yellow Taxis

(b) Green Taxis

(c) Ride-Hailing Services

(d) Subway Trains

Figure 1: Monthly volumes of pick-ups and drop-offs (for taxis and ride-hailing services) and entries and exists (for subway trains) from 2019 through 2022, inclusive.

3.1. Taxi and ride-hailing services

NYC operates two distinct types of taxis: YT[2] and the GT.[3] Their difference lies in their designated service regions. YTs have the exclusive privilege of accepting both street-hailing and prearranged passengers throughout the entirety of NYC's five boroughs. In contrast, GTs can only serve passengers in the borough of Manhattan above East 96th and West 110th Streets and in the remaining four boroughs. Moreover, while GTs face no constraints on drop-off locations, they are prohibited from accepting passengers at airports without prior arrangements being made. The taxi data contain attributes such as pick-up (O) and drop-off (D) timestamps and locations, with each origin or destination being aggregated to a unique taxi zone (TZ) identifier.[4] NYC ride-hailing services were also sourced from the trip record data published by the NYC Taxi and Limousine Commission (TLC) as submitted by the ridesharing companies. The structure of this dataset is similar to that of the taxi, with O and D locations reported by TZ.

[2] https://www.nyc.gov/site/tlc/businesses/yellow-cab.page
[3] https://www.nyc.gov/site/tlc/businesses/green-cab.page
[4] https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page

Cleaning of these data involved removing anomalous records from both taxi and RHS datasets. This included data with trip distances that were either negative or exceeded 200 miles, and those reporting trip durations shorter than one minute or exceeding four hours. We then calculated the cumulative number of O and D within each TZ for every month between 2019 and 2022 (see Figures 1a-1c). Considering the discrepancies between TZ and NTA geometries, a dasymetric mapping approach was employed to aggregate and re-assign values from TZs to NTA boundaries.

3.2. Subway train turnstile records

Subway turnstile usage data,[5] crucial for monitoring ridership flow, was collected from devices stationed at entry and exit points within the Metropolitan Transportation Authority's New York City Transit (NYCT) system. Turnstile volume is aggregated and reported every four hours documenting the number of individuals entering and exiting each station. These data were cleaned to remove implausible entry or exit counts. Specifically, values below zero or surpassing 7,200 passengers within a designated four-hour period were deemed improbable. This threshold was established based on the assumption that a passenger passes every two seconds, leading to a maximum of 7,200 passengers within a four-hour window. In such instances of erroneous data, we substituted the anomalous figures with the number of people from another turnstile at the same entry/exit point and at the same time at the given station. We then aggregated the entry and exit counts from each ST station for every month (shown in Figure 1d). Our final monthly ST entry and exit passenger flow for each NTA was determined based on the spatial intersection of the NTA with a 1,000-meter buffer around the ST stations, as walking is the most preferred option for distances up to 1000m (Hu et al., 2022). If a station's 1,000-meter buffer intersects with an NTA, the raw counts from that station are assigned to that NTA. If a single NTA intersects with the buffers of multiple stations, the values attributed to that NTA are derived from the mean of those intersecting stations' counts.

3.3. Explanatory variables used in regression analysis

The independent variables used in our regression analysis encompassed three dimensions: demographics and socioeconomics, built environment features, and Covid-19 case count. The last dimension is simply the cumulative count of individuals subjected to an antibody test[6] in each NTA over the course of our analysis period. The original data was reported at a spatial resolution of ZIP Code Tabulation Area (ZCTA) so regionally-weighted dasymetric mapping was used to re-allocate values to NTA.

3.3.1. Socioeconomic and demographic data

The socioeconomic and demographic characteristics of the NYC populous were extracted from the most recent American Community Survey (ACS) five-year dataset (2017-2021), collected by the U.S. Census Bureau.[7] An initial set of demographic and socioeconomic variables was curated. This selection process was informed by prior research in this domain (Ghaffar et al., 2020; Li and Yuan, 2022), supplemented by our own ideas as to what might be relevant in explaining changes in transportation patterns. We initially identified six categories:

- *Age*, encompassing the following cohorts: 0-24, 25-39, 40-64, and 65 and above;
- *Race*, consisting of categories White, Black or African American, Asian, and others;
- *Gender*, reported as either male or female.
- *Economic indicators*, with sub-variables of median household income, number of individuals possessing a bachelor's degree, and renter-occupied housing unit;
- *Car ownership*, specifically the number of households without a car;
- *Commute characteristics*, which cover the modes of driving alone, using a taxi, carpooling, biking, walking, utilizing public transportation (excluding taxis), and working from home.

3.3.2. Built environment data

Four types of built environment data were identified, representing aspects of density, diversity, design, and destination accessibility. *Density* is reported via the plot ratio[8] of all buildings within a neighborhood, indicating the collective volumetric occupancy of constructed spaces relative to the total area of the locale. *Diversity* is

[5] https://data.ny.gov/Transportation/Turnstile-Usage-Data-2019/xfn5-qji9
[6] https://data.cityofnewyork.us/dataset/DOHMH-Covid-19-Antibody-by-Modified-ZIP-Code-Tabul/6qs8-44ki
[7] https://data.census.gov/
[8] The ratio of the total floor area of all the buildings in one neighborhood to the size of the land area upon which the neighborhood is built.

quantified using Shannon entropy (Shannon, 1948) of land use[9] (e.g., Commercial & Office Buildings, Industrial & Manufacturing, Parking Facilities, etc.) present within a specific NTA. *Design*, is determined by the total number of street intersections of NYC's street centerline[10] within the boundaries of a given NTA. Finally, *Destination Accessibility* refers to the proportion of POI of a specific category, such as recreational facilities, commercial entities, health services, and so forth, in relation to the total number of POI within a given NTA. The POI dataset[11] is published by the Department of Information Technology & Telecommunications of NYC, which is a comprehensive compilation sourced from various agencies.

4. Methodology

This study's analytical framework comprises four principal steps shown in Figure 2, namely data collection and pre-processing, recovery rate calculation, k-means clustering, and a spatial lag regression model (SLM). Note that for uniformity, we henceforth refer to all vehicle pick-ups or turnstile entries as trip Origins (O) and all drop-offs or turnstile exits as trip Destinations (D). In later discussion of the Covid-19 pandemic in NYC, we refer to *three waves* as reported by Li et al. (2022). The first from March to June 2020 with strict anti-epidemic measures; the second from November 2020 to June 2021, enforcing gathering limits; and the third from December 2021 to February 2022, without restrictive policies.

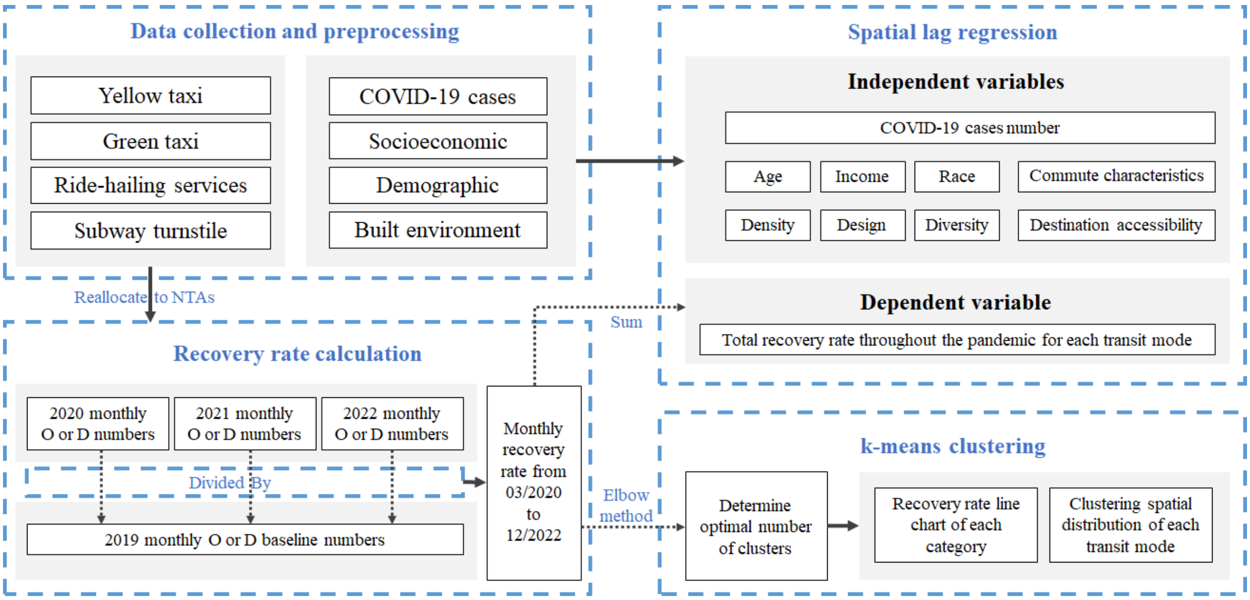


Figure 2: Analytical framework.

4.1. Calculating recovery and temporal clustering

To address `RQ1` we first computed the proportion of each month's trip O and D, from the onset to the end of the pandemic, in relation to the corresponding month in the pre-pandemic year of 2019. The resulting recovery value equals 1 if a transportation mode's activity for a month is equal to the activity of that same transportation mode in the month immediately prior to the pandemic. We designated this proportion as the *Recovery Rate* (R) and calculated it for O and D separately. We employ subscript notation to designate the mode of transportation and O vs. D. For instance, $R_O(YT)$ represents the origin recovery rate for yellow taxis. The reason for selecting a monthly interval to measure the recovery rate is that it offers a balance between granularity and trend identification. Monthly data provides enough detail to detect short-term fluctuations due to the changes in epidemic severity, yet it is sufficiently aggregated to reduce fluctuations that occur in the daily or weekly patterns.

[9] https://www.nyc.gov/site/planning/data-maps/open-data/dwn-pluto-mappluto.page
[10] https://data.cityofnewyork.us/City-Government/NYC-Street-Centerline-CSCL-/exjm-f27b
[11] https://data.cityofnewyork.us/City-Government/Points-Of-Interest/rxuy-2muj

In addressing RQ2, we employed k-means clustering to the combined O and D recovery rates for each transport mode within neighborhoods from March 2020 through December 2022. This was done in order to identify similarities in how transportation modes recovered in different neighborhoods. We could then determine which groups of neighborhoods responded in similar ways and if the spatial patterns of recovery were consistent across modes of transportation. The optimal number of k clusters was determined by running k-means multiple times with an increasing number k. The elbow method (Thorndike, 1953) was then used to identify the optimal number for each transportation mode, based on the aggregated distance at which clusters converge. Such an approach has been employed in related work (Cui et al., 2020) and involves plotting the within-cluster sum of squares against the number of clusters and looking for the point where the rate of decrease sharply changes. This point suggests that adding more clusters beyond this number does not improve the modeling of the data. Using this approach the most suitable number of k clusters for YT and GT was six, with three being most appropriate for RHS and ST (see figures in the Appendix).

4.2. Comparing to other indices

Given that our investigation of this topic was driven by the onset of the Covid-19 pandemic, we felt it was important to compare our transportation recovery rates against health data related to the pandemic as well as governmental regulatory action. According to a previous study, disparities in Covid-19 testing and positivity rates may bias correlation outcomes, especially during and following the initial 2020 wave (Lieberman-Cribbin et al., 2020). Therefore, we carried out a Pearson correlation analysis to examine the relationship between daily Covid-19 cases, hospitalizations, deaths, and the recovery rates of our four distinct transportation modes.

Similarly, we accessed the stringency index for the United States as reported from Oxford Covid-19 government response tracker project (Hale et al., 2021) and assessed the Pearson correlation between the index and our recovery rates. This stringency index [12] is a numerical index to measure the stringency of government responses and actions taken such as shutting down businesses, schools, and investment in health care. The values range between 100 (complete shutdown) to 0 (no government Covid-19 -related action).

4.2.1. Regression analysis

At this stage, each recovery rate, R, is represented by a sequential array of monthly values that are calculated as the proportion of pre-pandemic usage. In order to use recovery as the dependent variable for a regression model, we needed to reduce the dimensionality of the recovery rates and represent them as single *recovery values*, one for each combination of transportation mode, O and D, and in each neighborhood. To accomplish this, we summed all values in the monthly recovery rate arrays. This summation captures the resilience of transportation within a neighborhood from the onset of the pandemic and the subsequent pace of its recovery. For example, if a neighborhood begins its recovery sooner and sustains a higher recovery rate than other regions, its cumulative recovery value will surpass those neighborhoods that recover later. Furthermore, in instances where a neighborhood wasn't significantly impacted by the pandemic, resulting in a minor decline, our computed recovery value for that region will also be higher. A larger recovery value indicates either high resilience of that neighborhood's transport mode or a swift and robust recovery. To address RQ3, we then used these *recovery values* as dependent variables in a set of regression models. We refer to this *recovery value* using a lowercase r for the remainder of this work. For example, $r_O(YT)$ is the recovery value for yellow taxi trip origins.

Before conducting the regression analysis, we first calculated the variance inflation factor (VIF) of all independent variables to prevent issues of multicollinearity. A number of variables, namely those representing *age groups 25-39*, *40-64*, *65 and above*, *population holding bachelor's degrees*, *individuals utilizing public transportation (excluding taxis)*, *those driving alone*, *walking*, *car ownership*, *white demographic*, and both *male* and *female* genders, reported high VIF values. The *renter-occupied housing unit* variable failed to achieve statistical significance in all models. While a prior study by Jin et al. (2023) did demonstrate a significant positive correlation between this variable and ride-sourcing usage in Chicago, its applicability in identifying disparities in NYC's recovery rates of four transport modes was not evident. The variables included in our spatial regression models are listed in Table 1. All VIF values are below five.

Given the operational similarities of taxis and RHS, and to facilitate comparative analysis across various modes of transportation, the research scope was harmonized for these three modes of transportation. Areas with minimal taxi and RHS trips, such as Staten Island, Rikers Island, and City Island, among others, were omitted from our analysis. Similarly, urban parks, airports, cemeteries, beaches, and regions dominated by large stadiums and arenas were also

[12] `https://github.com/OxCGRT/covid-policy-dataset`

excluded due to the absence of residential population and census data. The finalized taxi and RHS research scope encompassed a total of 179 neighborhoods, including the boroughs of Manhattan, Brooklyn, Queens, and the Bronx. Due to the limited coverage of the ST station buffers in some neighborhoods, the scope of analysis for ST recovery was narrowed to 161 neighborhoods. This refinement in the research scope ensures a more focused and relevant examination of areas directly influenced by ST station proximity and accessibility.

We began our assessment by running a linear regression analysis on our eight dependent variables, namely all combinations of O and D recovery values with four modes of transportation. We then calculated *Global Moran's I* to identify spatial autocorrelation in our results. The Moran's I values were significantly higher than their respective Expected I, as detailed in the description of the dependent variables in Table 1. The findings denote a statistically significant positive spatial autocorrelation for all eight dependent variables. Thus, relying solely on simple linear regression proves to be insufficient for our analysis. We therefore used an SLM in order to account for spatial autocorrelation.

Table 1
Regression model variables and summary statistics. All dependent variable recovery rates are based on monthly values from March 2020 through December 2022.

Variable	Description	Mean	SD	Min	Max
Dependent variables					
$r_O(YT)$	Sum of monthly YT pick-up recovery rates, Moran's $I = 0.2502$, Expected I = -0.0056	9.671	5.134	4.213	50.566
$r_D(YT)$	Sum of monthly YT drop-off recovery rates, Moran's $I = 0.5868$, Expected I = -0.0056	11.758	1.626	8.568	16.304
$r_O(GT)$	Sum of monthly GT pick-up recovery rates, Moran's $I = 0.6005$, Expected I = -0.0056	2.591	1.908	0	10.678
$r_D(GT)$	Sum of monthly GT drop-offs recovery rates, Moran's I = 0.7444, Expected I = -0.0056	2.591	1.908	0	10.678
$r_O(RHS)$	Sum of monthly RHS pick-up recovery rates, Moran's I = 0.7394, Expected I = -0.0056	27.346	3.326	20.277	35.017
$r_D(RHS)$	Sum of monthly RHS drop-off recovery rates, Moran's I = 0.6919, Expected I = -0.0056	26.904	3.168	17.443	35.472
$r_O(ST)$	Sum of monthly ST entries recovery rates, Moran's $I = 0.8479$, Expected I =-0.0063	13.690	2.045	9.000	17.152
$r_O(ST)$	Sum of monthly ST exits recovery rates, Moran's $I = 0.6786$, Expected I =-0.0063	20.398	2.701	12.847	29.830
Independent variables					
Covid-19 features					
CaseNumber	The number of accumulated Covid-19 cases, as 10^4	0.518	0.320	0.086	2.007
Socio-economic and demographic characteristics					
PctAge0-24	The proportion of population below 24 years old	0.291	0.069	0.138	0.606
PctBlackAfrican	The proportion of Black or African American	0.239	0.253	0.006	0.905
PctAsian	The proportion of Asian	0.152	0.157	0.002	0.746
PctOtherRace	The proportion of some other racial minorities	0.155	0.134	0.003	0.589
MedianIncome	The median household income, as $\$10^6$/household	0.787	0.347	0.276	1.921
Commute characteristics					
PctCarpooled	The proportion of population commute by carpool	0.020	0.013	0.000	0.064
PctPublicTransp	The proportion of population commute by public transportation	0.230	0.067	0.057	0.406
PctTaxi	The proportion of population commute by taxi	0.005	0.005	0.000	0.027
PctBicycle	The proportion of population commute by bicycle	0.006	0.008	0.000	0.036
PctWFH	The proportion of population work from home	0.050	0.037	0.010	0.154
Built environment features					
PlotRatio	The plot ratio in each neighborhood	0.593	0.707	0.118	5.649
Intersection	The number of pedestrian network intersections in each neighborhood, as 10^3	0.840	0.543	0.160	3.242
LandUseMix	$LandUseMix = -\sum_{i=1}^{n} p(x_i)\log_n(p(x_i))$, x_i is one of the n land use types in each neighborhood. $p(x_i)$ is the proportion of the area of the ith type of land use in each neighborhood.	0.548	0.201	0.086	0.928
Destination accessibility					
PctResidential	The proportion of residential POI (of total POI)	0.230	0.108	0.015	0.600
PctEducationFacility	The proportion of education POI (of total POI)	0.160	0.097	0.000	0.892
PctRecreationalFacility	The proportion of recreational POI (of total POI)	0.079	0.091	0.000	0.629
PctCommercial	The proportion of commercial POI (of total POI)	0.057	0.097	0.000	0.574
PctGovernmentFacility	The proportion of government POI (of total POI)	0.076	0.066	0.000	0.423
PctHealthServices	The proportion of health services POI (of total POI)	0.034	0.029	0.000	0.157

5. Results

5.1. Descriptive analysis

The recovery rates of the total monthly trip *O* and *D* from 2020 to 2022 in comparison to the same months in 2019 are shown in Figure 3. Although this figure appears similar to Figures 1 at first glance, it actually depicts the recovery rates instead of row numbers, thus allowing us to visualize all modes of transportation on the same plot and therefore compare city-wide recovery across modes of transportation.

It is evident that since the onset of the first case of Covid-19 in NYC on March 1, 2020, the four modes of transportation have been significantly impacted, witnessing a decline that persisted through April of that same year. When compared with the ridership volumes of April 2019, it is clear that taxis were hardest hit by the pandemic.

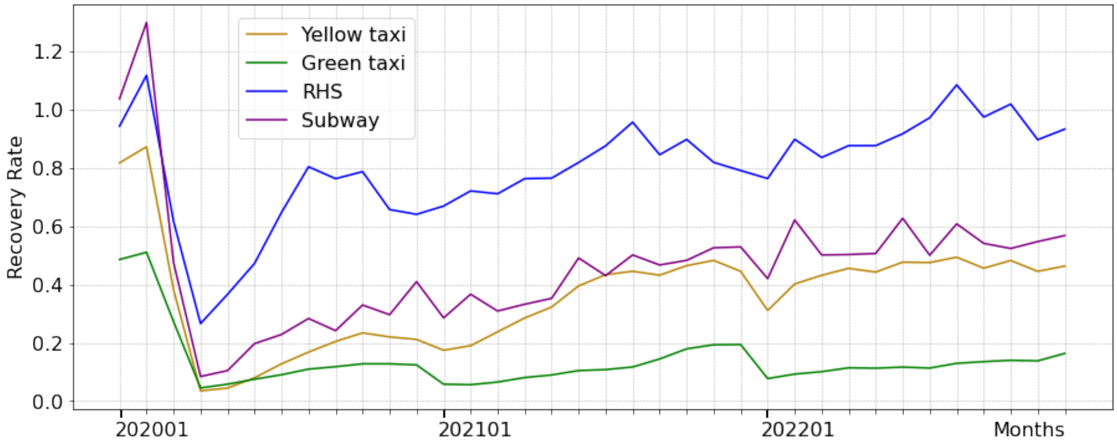


Figure 3: Recovery rates of our four transport modes from just prior to the start of the Covid-19 pandemic through 2022.

Table 2
Correlation matrix of recovery rate, stringency index and Covid-19 health data

	$R(YT)$	$R(GT)$	$R(RHS)$	$R(ST)$	Stringency	Cases	Hospitalizations	Deaths
$R(YT)$	1.000***	0.777***	0.828***	0.947***	-0.902***	-0.042	-0.345**	-0.446***
$R(GT)$	-	1.000***	0.436***	0.844***	-0.640***	-0.116	-0.200	-0.260
$R(RHS)$	-	-	1.000***	0.753***	-0.763***	-0.077	-0.515***	-0.654***
$R(ST)$	-	-	-	1.000***	-0.847***	-0.050	-0.309*	-0.395**
Stringency	-	-	-	-	1.000***	0.011	0.244	0.327*
Cases	-	-	-	-	-	1.000	0.585***	0.213
Hospitalizations	-	-	-	-	-	-	1.000***	0.819***
Deaths	-	-	-	-	-	-	-	1.000***

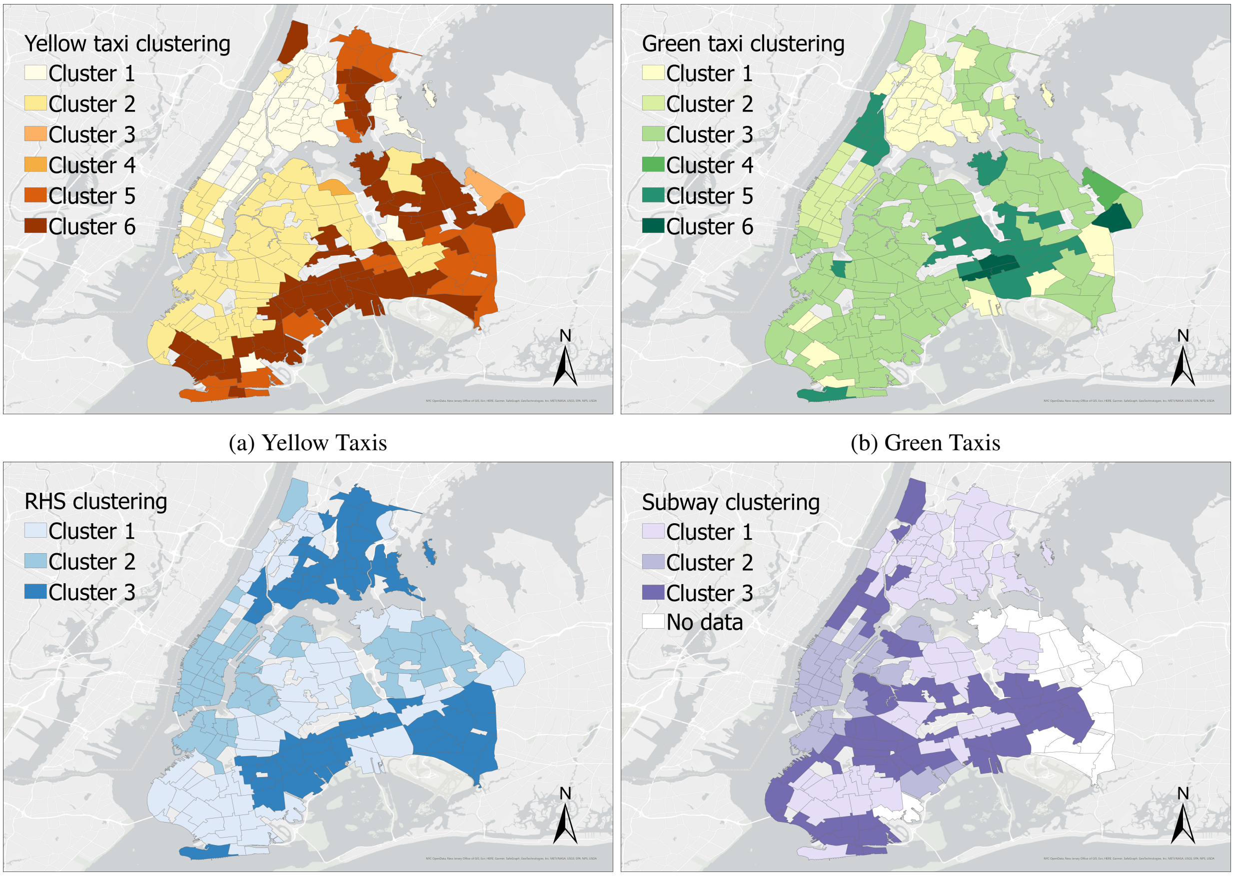
Note: * $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

In April 2020, both taxis and ST plummeted to 10% of the previous year's levels, whereas RHS demonstrated more resilience, sustaining 30% of the passenger volumes relative to the same month in the preceding year. An examination of the recovery rates during the later stages of the pandemic reveals varying degrees of resilience among the different transport modes. RHS demonstrated the most substantial recovery, nearly returning to pre-pandemic levels by July 2022. On the contrary, YT and the ST system faced a more gradual recovery, only managing to attain approximately half of their pre-pandemic volumes by the end of 2022. GT encountered a particularly challenging recovery, achieving only 20% of their previous operational levels. This highlights how the pandemic has exacerbated the decline of this mode of transportation.

The results of our correlation analysis exploring the relationships between our four transportation recovery rates, Covid-19 -related health data, and governmental stringency index are reported in Table 2. We found that the stringency index has a stronger correlation with the speed of transportation recovery compared to the actual number of Covid-19 cases, especially for ST, which are more influenced by policy than by the measured severity of the pandemic with respect to health. Among the three types of Covid-19 case counts, the death count reported a much higher correlation with the different recovery rates than the positive case counts.

5.2. Cluster analysis

The results of our k-means clustering were mapped to neighborhood boundaries and shown as a series of choropleth maps in Figure 4, one for each mode of transportation. While the k-means clustering analysis was done on the temporal recovery rates, these maps reveal that there are important spatial distribution trends across different modes of transport. In the clustering of three transport modes, apart from YT, Manhattan alone, or coupled with a few neighboring Brooklyn NTAs, emerged as a distinct *recovery region*. However, the distinction between downtown Manhattan and other regions is not as pronounced in the case of YT. Additionally, a clear demarcation between suburban and downtown areas is evident in the case of YT and RHS, while the other two transport modes do not exhibit an obvious urban-peripheral pattern. For taxis, both types exhibit exceptionally unique clusters (Clusters 3 and 4 for YT and Cluster 4 for GT). In contrast, RHS and ST not only lack outlier clusters, but the trends in their three clusters display a marked consistency and similarity in their patterns.



(a) Yellow Taxis

(b) Green Taxis

(c) Ride-hailing Services

(d) Subway Trains

Figure 4: Temporal clustering results of our four modes of transportation. While the clustering was based on temporal recovery rates, the maps show clear spatial clustering for these rates as well.

Figures 5-8 show O and D recovery rates of all neighborhoods within each individual cluster for every transport mode (in blue and gray), along with their respective medians (green and red). Notably, all y-axis are the same except for Clusters 3 and 4 of Figure 5 where the y-axis limit is set at 4.5.

5.2.1. Yellow taxi clustering

In the YT clustering (Figure 4a), Central and Northern Manhattan, along with the Southern Bronx, are categorized as Cluster 1, while Downtown Manhattan, Central, and Western Brooklyn fall under Cluster 2. Suburban areas predominantly belong to Clusters 5 and 6. The remaining Clusters, 3 and 4, are noteworthy. Each of these clusters consists solely of one neighborhood: East Elmhurst, adjacent to LaGuardia Airport (LGA), and the Douglaston–Little Neck area in Northeastern Queens. We observe that Clusters 1 and 2, located in the core of NYC, consistently exhibit higher D recovery rates compared to O over the three-year period. However, the peripheral Clusters 5 and 6 displayed a O recovery rate much higher than the D rate following the end of the third wave of infections, particularly in the most remote suburban areas, Cluster 5. This suggests that post-pandemic, as normalcy resumes, more individuals residing in the suburbs opted for taxis to commute downtown.

Cluster 3 is unique due to its location in the Douglaston–Little Neck neighborhood, a renowned leisure and tourism destination, home to Douglaston Golf Course. Coupled with the absence of nearby ST stations in Northeastern Queens

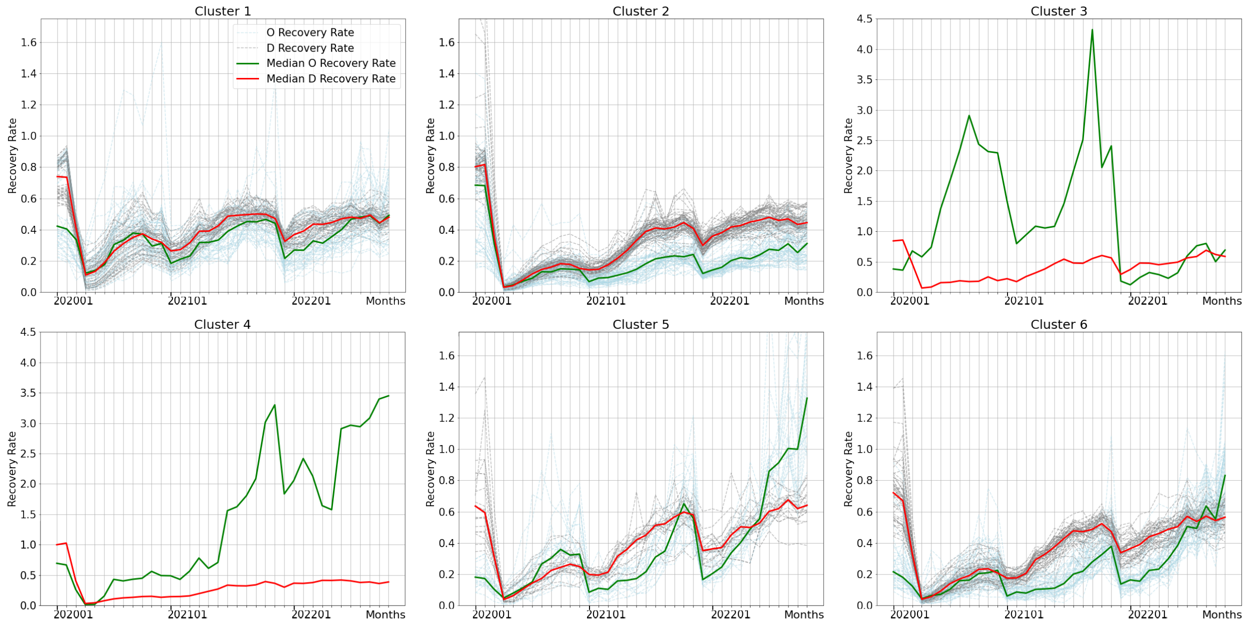


Figure 5: Recovery rates for Yellow Taxis shown as six clusters.

and a significant Asian population – who were particularly cautious during the pandemic (Anand et al., 2023) – this area witnessed a surge in O recovery rate. Many who previously relied on buses or ST likely shifted to using taxis, resulting in a notable increase in O volumes for both YT and GT in this neighborhood during the pandemic. Similarly, Cluster 4 is exceptional due to its proximity to LaGuardia Airport (LGA).[13] Through these data, it can be seen that the airport, severely impacted in April 2020, began to rebound swiftly, with O recovery rates surging beyond pre-pandemic levels by July 2021. This surge can be attributed to the relaxation of New York's epidemic prevention policies following the second wave, resulting in a significant influx of travelers from within the United States and Canada into NYC, a trend that persisted until the end of 2021. The O volumes in December even tripled compared to those of December 2019. Although this trend saw a decline during the peak of the third wave in January and June, a rapid rebound was once again observed, indicating that the pandemic did not substantially impede inter-city mobility within North America, and the number of entrants to NYC from the United States and Canada post-pandemic was even higher than before. However, this neighborhood did not exhibit uniqueness in the case of GT because GT is not permitted to pick up passengers at the airport.

5.2.2. Green taxi clustering

The recovery rate trends of GT in Clusters 1, 3, and 5 are markedly similar, predominantly occupying neighborhoods across the Bronx, Brooklyn, and Queens (see Figure 4b). In the Bronx's Cluster 1, the recovery was relatively resilient during the first and second pandemic waves, but after the third wave, the recovery decelerated. By comparison, Cluster 5, encompassing Northern Manhattan and central-southern Queens, displayed a milder impact from the third wave, manifesting a more robust recovery trajectory compared to Cluster 1. However, neighborhoods within Brooklyn and northern Queens' Cluster 3 experienced substantial setbacks across each pandemic wave, coupled with a markedly languid recovery pace.

In downtown Manhattan, where GT is not permitted to pick up passengers, a natural clustering emerged as a distinct group. Within these zones, $R_D(GT)$ exhibited swift ascensions following each pandemic wave. This trend parallels $R_D(YT)$ in these regions, although more moderate. An intriguing observation can be made in Cluster 6, particularly in the Bellerose neighborhoods adjacent to Alley Pond Park, and those proximate to the southern boundary of Forest Park. These areas saw a substantial volume of O, as well as a similar recovery trend in D during waves one and two of the pandemic, albeit with a more moderate increase compared to the O recovery rates. However, these neighborhoods

[13]LGA is the smallest major airport in the New York area, handling domestic and limited international flights.

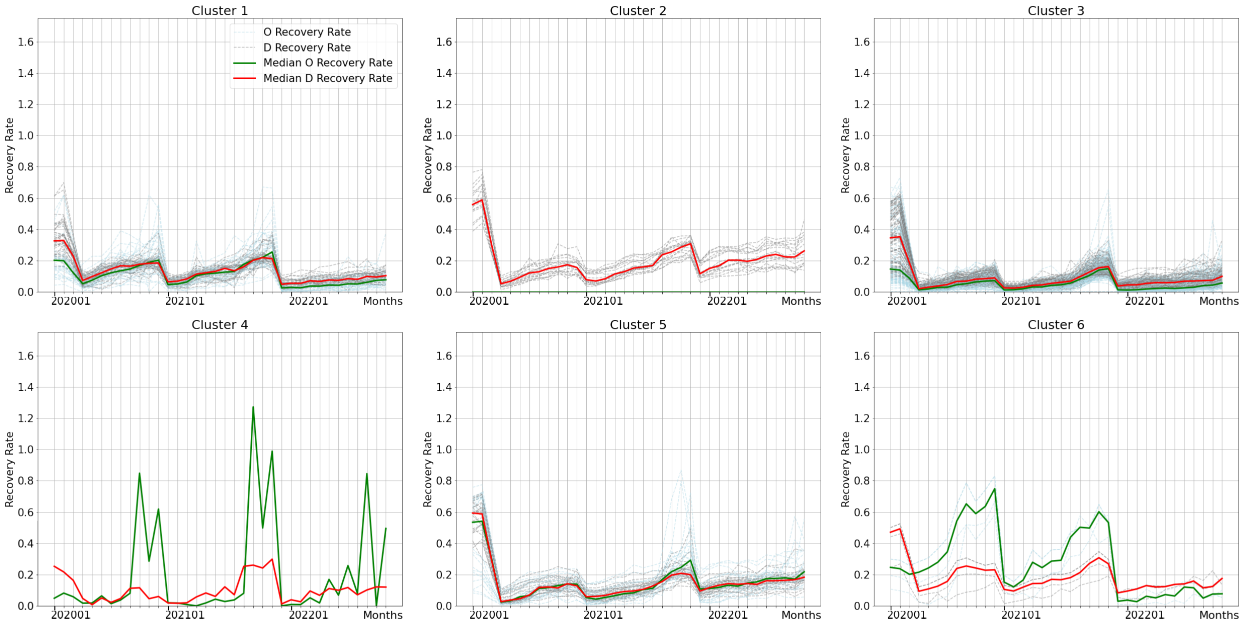


Figure 6: Recovery rates for Green Taxis shown as six clusters

experienced a decline in trip flow following the end of the third wave. This trend is likely due to the fact that the southern entrances of these parks are closer to the mentioned neighborhoods. During the pandemic, many people visit suburban parks for leisure and activities, leading to more O and D in these areas. After the pandemic, however, the number of visitors to these parks decreased, which is shown by the reduced number of trips in these neighborhoods.

5.2.3. Ride-hailing services clustering

The $R(RHS)$ of the three clusters show very similar trends (Figure 7), differing primarily in intensity. Cluster 3, located in the suburbs (Figure 4c), has recovered the fastest. Downtown Manhattan and the central-northern part of Queens are quite similar and ranked second in terms of recovery, while Cluster 2, in the middle parts of NYC, has been the slowest to recover. Although Cluster 2 recovered to almost the same level as Clusters 1 and 3 after the end of the third wave of the pandemic, neighborhoods in this category experienced the most severe drop in passenger volume during each serious wave of the pandemic. Especially during the first wave in 2020, these types of neighborhoods only recovered to 60% in August 2020, while the other two types of neighborhoods recovered to 80% and 100% in the same month. This is consistent with Cluster 2 of YT and Cluster 3 of GT; they are both located between downtown and the suburbs and have similar recovery rate patterns, being hit hardest during the first wave of the pandemic and showing lower resilience during recovery.

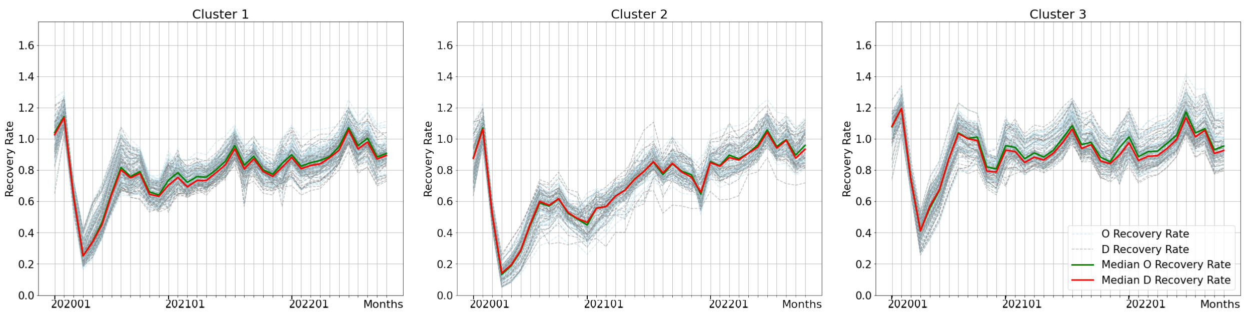


Figure 7: Recovery rates for Ride-hailing Services shown as three clusters

Furthermore, in these three clusters, $R_O(RHS)$ and $R_D(RHS)$ are very similar in each cluster. Only in the suburban Cluster 3, $R_O(RHS)$ is slightly higher than $R_D(RHS)$. However, RHS has not generated any special neighborhoods near airports or large parks. This is likely due to the advance booking required by RHS. In contrast, passengers getting off flights or finishing park visits often choose the immediately available YT waiting at the airport or park gates.

5.2.4. *Subway train clustering*

The recovery plots of the ST and RHS are similar, with three types of recovery rate trends being alike (Figure 8), but the intensity of recovery varies across different geographic locations (see Figure 4d) and clusters. The ST does not reach very remote urban areas, such as the northeastern part of Queens. Thus, the areas in Cluster 1, located in the northern Bronx, central Queens, and southern Brooklyn, are already considered the farthest reaches of the ST system. Similar to the previous three transport modes, Cluster 1 recovered the fastest after being hit by the pandemic.

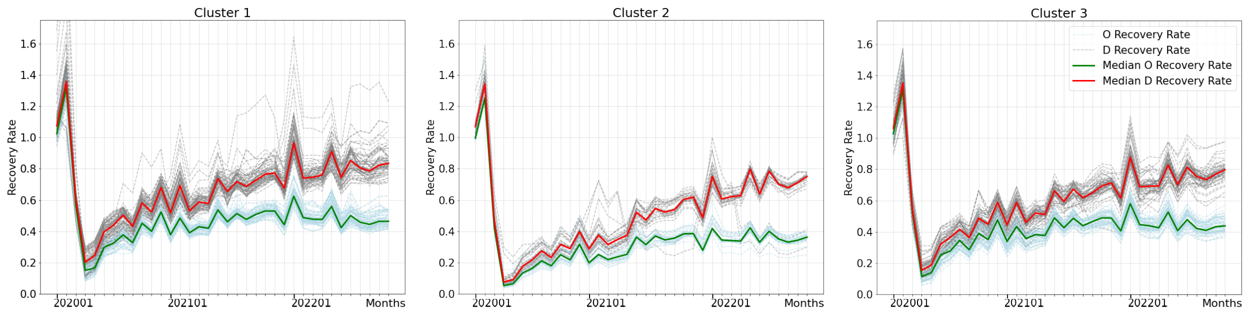


Figure 8: Recovery rate of Subway Trains shown as three clusters

Yet, unlike the other three, Cluster 2 located in downtown Manhattan recovers the slowest. This may be due to the operational range and travel characteristics of the ST system. The middle district of the taxi operation range equates to the *suburbs* of the ST. Moreover, people who already live downtown and don't require long-distance commuting might choose walking, biking, or taking a taxi to avoid mass public transportation during the pandemic. This results in the ST stations downtown having a generally slower recovery speed compared to other areas.

5.3. Regression results

A total of eight SLM models were developed, corresponding with each of the four modes of transportation and trip O and D. We examined the Akaike Information Criterion (AIC), log-likelihood, and significance of coefficients for all of our models and discussed the results of each model in this section. The regression results are presented in Table 3. In exploring the models, it is clear that both the O and D models for RHS are well-fitted. Both have high values for pseudo-R-squared and spatial pseudo-R-squared. The O (entry) model for the ST outperforms the D (exit) model. The former achieves a pseudo R-squared near 0.9, whereas the latter is close to 0.7. The independent variables contribute less to our four taxi models. While the GT's O and D models have high pseudo-R-squared values, their spatial pseudo-R-squared values hover around 0.4. This indicates that $r_O(GT)$ and $r_D(GT)$ have high spatial dependence and are likely influenced by additional factors (e.g., policy restrictions). The O model for YT has both pseudo-R-squared and spatial pseudo-R-squared values around 0.3. These metrics for D are substantially higher, which is the inverse of the ST models.

When comparing the impact of each major category of variables across different transport modes, in general, *race* has the broadest impact, showing significant correlations with all transport modes. Commute characteristics are significantly correlated with taxis and RHS but seem to have little impact on the ST model. Built environment features are closely related to the recovery of both RHS and ST, but show no correlation with either YT or GT. Finally, as expected, destination accessibility has the highest correlation with RHS and the least with ST.

In addition to the regression analysis presented in this section, we also analyzed the Pearson correlation of the non-significant independent variables with our dependent variables across our models. While a few of the non-significant variables exhibited correlations with our recovery patterns, the focus of this work is on investigating the combination of variables and how they relate to recovery. Nevertheless, we report on the correlations in Appendix Table 4.

5.3.1. Covid-19 features

The accumulated Covid-19 cases in each neighborhood correlate significantly and positively with $r(ST)$ and $r_D(GT)$. This should not suggest that higher infection numbers are beneficial to the ST's recovery, as Table 2 illustrates that the ridership trends of the ST are negatively correlated with all categories of case counts. Rather, it indicates that neighborhoods with a substantial reliance on ST may exhibit higher recovery rates due to the consistent demand for these services. Although the frequent use of ST could serve as a catalyst for the service's recovery, this increased utilization does not come without drawbacks. It could concurrently elevate the potential for Covid-19 spread due to the denser population of individuals using public transit. This underscores the complex interplay between transport reliance and public health dynamics during a pandemic, where increased service usage for essential mobility can inadvertently align with heightened transmission risks. However, no analogous outcomes were observed in the $r(YT)$ and $r(RHS)$.

5.3.2. Socio-economic and demographic characteristics

Aside from the racially White population, the impact of other racial groups on recovery value varies. The recovery value of transport modes that significantly correlate with Black or African American individuals, as well as other racial minorities, is consistently positive. Intriguingly, Black or African American populations only show a significant positive correlation with $r(RHS)$, while the category "some other race" is positively correlated with the other three transport modes. The proportion of the Asian population in an area, similar to income levels, only shows a significant negative correlation with $r_D(YT)$. This indicates that in communities where the income is higher or there is a larger Asian population, the $r_D(YT)$ is slower. Regarding Age, areas with a larger percentage of the population under 24 years show a deceleration in the recovery rate across all transport modes. Notably, $r(YT)$ and $r(GT)$ appear to be the most adversely affected.

5.3.3. Commuting characteristics

The proportion of people taking public transportation to work exhibits a strong negative correlation with the recovery of all vehicular transport modes, except for $r(ST)$. The rate of bicycling to work shares similar regression results with public transportation, showing negative correlations with both taxis and RHS. However, its significance is only evident in $r_D(YT)$ and $r_D(GT)$. The choices to carpool to work or work from home both have a pronounced negative correlation with $r(RHS)$, as more people opt to carpool using private vehicles or work directly from home, there's a reduced demand for hiring vehicles during the pandemic. As expected, the proportion of individuals using taxis correlates positively with the recovery capability of taxis and RHS. Upon examining the spatial distribution of taxi usage, we found that areas with the highest proportions are all concentrated in downtown Manhattan. These areas are locations where GT cannot pick up passengers, so the negative correlation for model III in Table 3 might be a unique artifact.

5.3.4. Built environment features

High values of the plot ratio are concentrated in downtown areas, while low values are predominantly found in the suburbs. Consequently, this variable shows a significant inverse relationship with both RHS and ST. The largest number of intersections is in the southeastern part of Queens and is lowest in the southern portion of Brooklyn. As expected, it positively correlates with $r(RHS)$ and negatively with $r(ST)$. What is particularly surprising among the built environment variables is the absence of any correlation between the Land Use Mix and r of various transport modes. This is not exclusive to NYC, as former studies have also shown that land use diversity does not correlate with Seoul's rail transit ridership (Sung et al., 2014).

5.3.5. Destination accessibility

The proportion of residential POI positively correlates with all models, with the coefficient being highest in the $r_O(YT)$. The proportion of health services-related POI shows a marked positive correlation with $r(RHS)$, possibly due to people's inclination to use RHS services for hospital and doctor visits. For the remaining POI categories (such as education, government, recreational, and commercial facilities), wherever they are significant in their respective models, the correlations are negative. This suggests that during the pandemic, entertainment activities, education, and political activities were severely impacted. The locations of these non-essential activities did not contribute to a rapid recovery in transportation during the pandemic.

Table 3
The results of our spatial lag regression models for four transport modes and trip origins and destinations.

Variables	YT model		GT model		RHS model		ST model	
	I.(O)	II.(D)	III.(O)	IV.(D)	V.(O)	VI.(D)	VII.(O)	VIII.(D)
Covid-19 features								
CaseNumber	-0.288	0.105	-0.162	0.365**	-0.128	-0.121	0.658***	1.639***
Socio-demographic characteristics								
PctAge0-24	-30.762***	-1.956	-1.880	-2.131*	-1.594	-0.226	-0.564	-0.375
PctBlackAfrican	3.071	-0.698	0.373	0.039	2.887***	3.163***	0.405	0.787
PctAsian	-3.687	-3.418***	0.618	0.012	-1.006	-1.195	1.186	-1.692
PctOtherRace	13.512***	-1.560	2.164*	1.196*	1.212	0.885	1.927***	3.918***
MedianIncome	0.259	-1.469***	-0.586	-0.321	0.502	0.103	0.714	0.546
Commute characteristics								
PctCarpooled	-43.454	7.265	6.832	-0.747	-41.426***	-38.003***	-4.616	19.168
PctTaxi	-7.245	32.578*	-60.830**	42.440***	72.582**	90.024***	21.004	-41.343
PctBicycle	-74.109	-31.337**	-20.074	-23.470**	-21.745	-8.366	-8.845	11.642
PctPublicTransp	-45.503***	-6.306***	-3.667*	-3.749***	-4.886**	-4.843**	0.475	1.273
PctWFH	25.319	3.819	9.083	7.338	-21.471**	-20.620**	-8.168*	-7.966
Built environment features								
PlotRatio	-0.659	-0.020	0.125	-0.116	-0.689***	-0.466*	-0.381***	-0.508*
Intersection	-0.707	-0.100	0.114	0.102	0.538***	0.685***	-0.402***	-0.612**
LandUseMix	1.303	0.413	0.602	0.743	0.289	0.106	-0.575	0.444
Destination accessibility								
PctResidential	6.127*	1.285*	1.735*	0.174	0.931	1.833*	1.248**	2.135*
PctEducationFacility	-3.748	0.925	-1.921**	1.080	-2.067*	-1.770*	0.040	0.415
PctRecreationalFacility	2.335	-1.730*	-1.816*	-1.069*	-1.735	-0.602	-0.641	0.184
PctCommercial	2.736	0.132	-0.644	0.362	-5.768***	-5.921***	-0.189	-0.779
PctGovernmentFacility	-8.895*	-2.196*	-1.312	-0.524	-1.033	-1.585	-1.616*	-0.548
PctHealthServices	-15.882	-0.022	-1.876	-1.771	11.057***	10.960***	2.903	-5.630
AIC	1068.474	562.206	624.874	458.22	672.412	688.636	397.976	638.436
Log-likelihood	-512.237	-259.103	-290.437	-207.113	-314.206	-322.318	-176.988	-297.218
Pseudo R-squared	0.3202	0.6368	0.6319	0.7879	0.8316	0.794	0.8946	0.6942
Spatial Pseudo R-squared	0.3138	0.5076	0.419	0.4865	0.7878	0.7606	0.7984	0.6484

Note: * $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

6. Discussion

This study presents several important findings. In our preliminary analysis, we anticipated that the cumulative number of Covid-19 cases would negatively impact local transportation recovery (RQ1), as prior studies had suggested that a higher number of Covid-19 cases corresponded to a significant decline in transport ridership (Li and Yuan, 2022). The reality in NYC proved to be quite different when it comes to transportation recovery. Our analysis revealed that the recovery of both Taxi and RHS had minimal association with the Covid-19 case numbers. This finding is also supported by research conducted in other cities, which revealed that people's inclination toward public transit is not highly sensitive to fluctuations in Covid-19 case numbers (Xiao et al., 2022). Actually, the most significant factors affecting the speed of transportation recovery during the pandemic are the stringency of government anti-pandemic policies and the socio-economic characteristics of the residents in a region. However, the latter cannot be rapidly adjusted in the short term. Therefore, the most effective approach for transportation agencies would be to develop more efficient, safe, and equitable travel policies for such exceptional times. This might include strategies like reopening public transportation and public activities at appropriate times, providing subsidies to taxi drivers during specific periods to serve poorer populations in remote suburbs, and making secure transport modes more affordable during peak pandemic periods.

Additionally, although ST recovery displayed a strong positive correlation with Covid-19 cases in our study, demonstrating that neighborhoods with higher public transportation ridership had higher Covid-19 infections (Harris, 2020; Cordes and Castro, 2020). It can be argued, at least in the long term, that the cumulative count of positive cases does not substantially influence mobility behavior in the area. With respect to the presence of health services, our findings align with those of Halvorsen et al. (2023), who found that the presence of hospitals did not significantly influence variations in NYC's ST ridership. Nevertheless, the proportion of available health services exhibited a highly significant and robust correlation with the recovery rate of RHS.

Our analysis also demonstrates that while both taxis and RHS are for-hire vehicle services, they should not be conflated. RHS has demonstrated the most resilience and significant recovery among the four transportation modes examined. This observation aligns with the findings of Bian et al. (2022), who noted that the initial three months of the pandemic had a more severe impact on traditional taxis compared to RHS. They further discovered that after NYC's reopening in June 2020, the volume of RHS passengers started to increase, whereas taxi ridership remained essentially unchanged from pre-opening levels, a phenomenon that we also observed. Our analysis, moreover, suggests that, following the initial wave of the pandemic, there was a gradual recovery in the ridership of YT. In contrast, the pandemic further accelerated the decline of green taxis, a downturn that had begun prior to the pandemic due to the prevalence of RHS. As numerous previous studies highlighted before the pandemic, the rise of services like Uber led to a decline in NYC taxi ridership (Willis and Tranos, 2021; Correa et al., 2017). We hypothesize that RHS has not only substituted a portion of the YT market but has also overwhelmingly dominated the market that was initially held by GT. This could be attributed to the conveniences offered by RHS, such as advance booking and doorstep pickup, which are particularly appealing to commuters in suburban areas, which traditionally should have been the primary clientele for GT. This trend was clearly further exacerbated by the pandemic. There hasn't been a resurgence in GT trips even after the pandemic ended.

Furthermore, we observed that after the initial outbreak in March 2020, RHS trips consistently mirrored the arrival of pandemic waves, reporting earlier than taxis and ST. During the peak times in January 2021 and January 2022, RHS did not experience the same precipitous declines seen in the other modes of transportation. Instead, they managed a smoother transition through these periods, swiftly rebounding thereafter. This observation presents a strategic opportunity for transportation agencies. Given that the RHS market typically responds more swiftly to the peaks of COVID-19 compared to taxis, monitoring the daily order volumes of RHS during similar exceptional periods can provide crucial insights. This proactive approach can serve as an early warning system, enabling agencies to formulate timely strategies. Such strategies could significantly mitigate government losses and, importantly, contribute to more effective containment of virus transmission. By leveraging these insights, transportation agencies can enhance their preparedness and response mechanisms for future public health crises.

In addressing `RQ2`, our analysis found that the four different modes of transportation exhibited important spatial differences in their recovery. For taxis and RHS, NTAs situated between downtown and the suburbs experienced the slowest recovery. However, for the subway, the slowest recovery was observed in the city center. However, across all four transportation modes, the suburban areas showed the quickest recovery, with the Bronx borough consistently exhibiting a notably high recovery rate. This borough has historically been home to a large racial minority population and hosts individuals from the city's lowest-income group. Our results suggest that in order to sustain a basic livelihood, these individuals had no choice but to either maintain their pre-pandemic commuting habits or, for those who could afford it, shift from public transit to taxis or RHS. Due to economic constraints and high rental burdens, we argue that many in this community could not opt for remote work, pause work, or flexibly adjust their modes of transportation during the pandemic (Fu and Zhai, 2021). As a result, either the impact on mobility was minimal or the recovery was swift. The results of our regression analysis support this, indicating that regions with higher proportions of Black or African Americans and other races, coupled with lower median incomes, facilitated quicker transportation recovery (`RQ3`). This observation confirms many prior studies. For instance, research has shown that most low-income individuals had limited flexibility in reducing their mobility (Ruiz-Euler et al., 2020; Dadashzadeh et al., 2022) and business visitation patterns changed less for these populations during the pandemic (McKenzie and Mwenda, 2021). Interestingly, a study conducted five years before the pandemic also found a negative correlation between NYC's median income and taxi ridership (Qian and Ukkusuri, 2015). These findings suggest that transportation resilience may not solely hinge on the inherent characteristics of a transport mode or policies formulated by the transport sector during crises. Rather, a significant determining factor might be the unique traits of community members and their unyielding basic needs. Thus, when observing swift mobility recovery in specific areas following significant disruptions and turmoil, it may not necessarily be a positive signal. Delving into the underlying reasons is crucial. It is paramount to acknowledge the difficulties facing lower-income and mobility-limited communities during major health crises and continue to improve policies aimed at transportation equity.

Finally, there are limitations to this work that must be acknowledged. One issue relates to the quality of the ST turnstile data set. We observed that, prior to the pandemic, the total number of ST turnstile entries exceeded exits. However, post-pandemic, exits surpassed entries, with an increasing gap between the two. A plausible explanation for the pre-pandemic scenario, where entries were approximately 20% higher than exits, might be due to congestion during peak hours. As ST stations become crowded, many passengers bypass the turnstile and exit through "emergency" gates, a situation that is not accounted for in the count. Post-pandemic, the fact that exits exceeded entries can potentially be attributed to a significant increase in fare evasion. Official data from the MTA reports fare evasion rates at around 14%.[14] Thus, there might be a discrepancy in the MTA's fare evasion statistics. Regardless, while these data have been used in numerous other studies, this discrepancy must be acknowledged (Vertes, 2023). Another limitation is this study employs data derived from the ACS, which contains inherent uncertainties and margins of error. Our methodology did not include specific techniques to adjust these errors during the data reassignment process. Therefore, it's important to consider these errors when interpreting our research conclusions and applications. Moreover, in allocating subway entries and exits, we directly selected a radius of 1000 meters as the service buffer. This choice of service buffer radius around subway stations is a critical factor that may have influenced our analysis results, particularly in more sparsely serviced areas, such as certain parts of Queens, Brooklyn, and the Bronx. In future research, we plan to experiment with different radii or improved allocation methods to refine our approach. Further, due to the inability to collect bus boarding and alighting data at the stop level, we could not incorporate buses into our comparative analysis. Similarly, bike-sharing data were not analyzed, given that the operational extent of NYC's *Citi Bike* is quite limited compared to the modes of transportation we analyzed.

While we examined four modes of transportation, our models were estimated based on the origins and destination numbers of trips. Future studies should consider modeling flows between origins and destinations. Additionally, our analysis was conducted with monthly data, but subsequent studies could benefit from examining recovery patterns on a finer temporal scale, such as weekly or daily. Crucially, future studies stand to gain significant insights by exploring the relationship between urban transport recovery rates and remote working at a more granular level, as well as the implications of travel demand models. This exploration could encompass a thorough analysis of trip production and attraction rates, coupled with an evaluation of how land use changes impact these factors. Last, given the *case study* nature of this work, the findings are specific to NYC but there are lessons to be learned for other cities. Subsequent studies should explicitly consider data from other cities for comparison, especially medium and smaller cities, to validate the causal relationships between these factors and enhance our understanding of variation in transportation resilience during a global pandemic.

7. Conclusion

In this study, we investigated the Covid-19 recovery patterns of four modes of transportation in New York City, namely yellow taxis, green taxis, ride-hailing services, and subway trains. We examined how monthly ridership patterns for these four modes changed between 2019 and 2022, producing a series of recovery rates split by trip origins and destinations as well as across neighborhoods. Through our analyses, we find that there are significant differences in how each mode of transportation responded to, and recovered from, the Covid-19 pandemic, and that recovery rates were not uniform across the entire city. In fact, there were important regional differences in how each mode of transportation recovered from the pandemic, and these recovery rates clustered across neighborhoods. With the goal of identifying factors contributing to differences in modal and regional recovery rates, we developed a set of spatial regression models that identified socioeconomic, demographic, and built environment factors that partially explain the differences in recovery rates. Our findings agree with existing work in this domain but go beyond what has been demonstrated previously by analyzing recovery over the course of the entire Covid-19 pandemic and between neighborhoods in a major U.S. city. Overall, the findings of our work provide valuable insight into how various modes of urban transportation uniquely respond to a global pandemic. Our work sheds light on the factors that influence urban resilience and recovery and suggests that further attention should be paid to certain socio-economic and demographic populations when studying transportation recovery. These findings will contribute to the development of more effective, equitable urban recovery policies, guiding enhancements in transportation infrastructure regulation to bolster resilience and recovery in response to future health emergencies.

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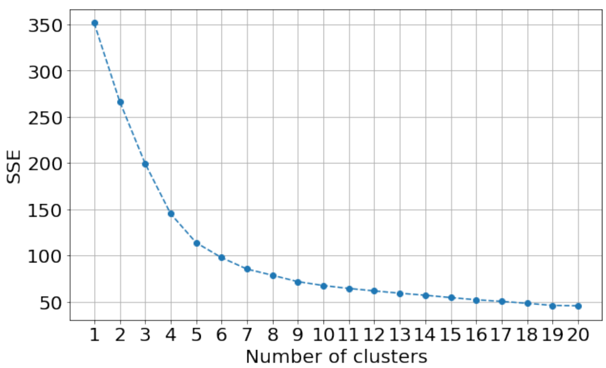
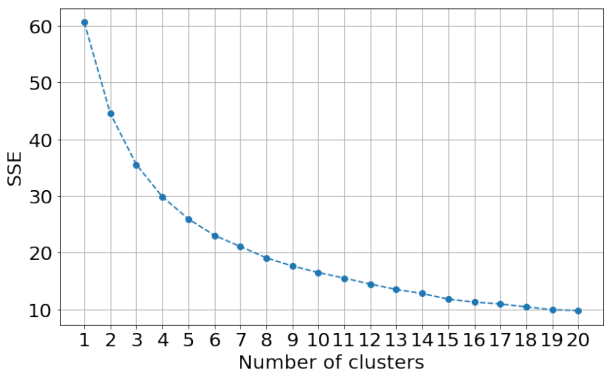
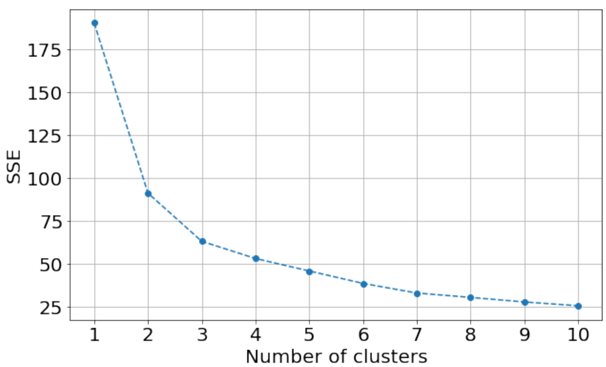
Appendix



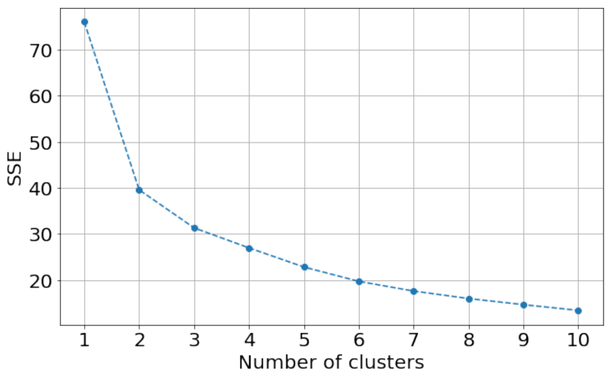
(a) Yellow Taxi



(b) Green Taxi



(c) Ridehailing Services



(d) Subway Train

Figure 9: The results of the Elbow Method for determining the optimal number of clusters in our k-means recovery rate analysis.

Table 4
The results of Pearson correlation for all variables in the eight models.

Variables	$r_O(YT)$		$r_D(YT)$		$r_O(GT)$		$r_D(GT)$		$r_O(RHS)$		$r_D(RHS)$		$r_O(ST)$		$r_D(ST)$	
	Coef	P	Coef	P	Coef	P	Coef	P	Coef	P	Coef	P	Coef	P	Coef	P
CaseNumber	-0.162	0.030	-0.084	0.266	-0.040	0.596	0.046	0.541	-0.169	0.023	-0.164	0.029	0.188	0.017	0.218	0.005
PctAge0-24	-0.052	0.493	0.304	0.000	0.230	0.002	-0.153	0.041	0.382	0.000	0.353	0.000	0.428	0.000	0.396	0.000
PctBlackAfrican	0.070	0.355	0.309	0.000	0.038	0.609	-0.142	0.058	0.702	0.000	0.711	0.000	0.204	0.009	0.191	0.015
PctAsian	-0.053	0.477	-0.310	0.000	0.109	0.145	-0.053	0.485	-0.392	0.000	-0.413	0.000	0.115	0.147	-0.119	0.134
PctOtherRace	0.167	0.026	0.263	0.000	0.426	0.000	0.140	0.062	0.297	0.000	0.264	0.000	0.455	0.000	0.547	0.000
MedianIncome	-0.035	0.641	-0.396	0.000	-0.391	0.000	0.139	0.063	-0.512	0.000	-0.461	0.000	-0.629	0.000	-0.587	0.000
PctCarpooled	0.079	0.292	0.025	0.743	0.221	0.003	-0.256	0.001	-0.013	0.860	-0.070	0.352	0.500	0.000	0.278	0.000
PctTaxi	0.053	0.479	-0.080	0.287	-0.420	0.000	0.422	0.000	-0.234	0.002	-0.136	0.069	-0.597	0.000	-0.528	0.000
PctBicycle	-0.177	0.018	-0.372	0.000	-0.385	0.000	0.073	0.333	-0.486	0.000	-0.430	0.000	-0.623	0.000	-0.379	0.000
PctPublicTransp	-0.249	0.001	-0.285	0.000	-0.115	0.126	0.062	0.409	-0.155	0.038	-0.125	0.096	-0.266	0.001	-0.039	0.626
PctWFH	-0.126	0.094	-0.388	0.000	-0.397	0.000	0.243	0.001	-0.630	0.000	-0.566	0.000	-0.748	0.000	-0.563	0.000
PlotRatio	0.014	0.849	-0.148	0.049	-0.349	0.000	0.415	0.000	-0.433	0.000	-0.334	0.000	-0.637	0.000	-0.518	0.000
Intersection	0.010	0.898	-0.110	0.141	0.016	0.833	0.042	0.580	0.174	0.020	0.194	0.009	-0.125	0.113	-0.195	0.013
LandUseMix	-0.103	0.169	0.030	0.692	-0.089	0.238	0.322	0.000	-0.187	0.012	-0.148	0.049	-0.376	0.000	-0.064	0.418
PctResidential	0.128	0.087	-0.028	0.710	0.305	0.000	-0.017	0.821	0.062	0.411	0.060	0.428	0.274	0.000	0.281	0.000
PctEducationFacility	-0.023	0.760	0.038	0.612	-0.175	0.019	0.008	0.918	-0.085	0.257	-0.092	0.220	-0.009	0.914	-0.041	0.605
PctRecreationalFacility	0.081	0.278	-0.140	0.062	-0.252	0.001	0.075	0.318	-0.211	0.005	-0.150	0.044	-0.218	0.006	-0.225	0.004
PctCommercial	0.032	0.673	-0.057	0.451	-0.108	0.151	0.174	0.019	-0.324	0.000	-0.319	0.000	-0.239	0.002	-0.213	0.007
PctGovernmentFacility	-0.138	0.065	-0.128	0.087	0.007	0.923	-0.205	0.006	0.018	0.807	-0.026	0.734	0.120	0.129	0.069	0.384
PctHealthServices	-0.148	0.048	0.071	0.346	-0.013	0.867	-0.178	0.017	0.223	0.003	0.205	0.006	0.137	0.082	0.051	0.521

As presented in Table 4, we performed Pearson correlation analysis on all independent and dependent variables. Notably, the variables highlighted in red exhibit high coefficients and significant Pearson correlations yet were deemed non-significant in the SLG. Variables such as PctAsian, MedianIncome, PctBicycle, and PctWFH display a consistent negative correlation in the specified models. This suggests that neighborhoods with a higher population of Asian residents, higher household incomes, more bicycle commuters, or more individuals working from home may experience a slower transportation recovery. However, variables like Intersection, LandUseMix, and all variables in Destination Accessibility still did not show a strong correlation with any dependent variables in the Pearson correlation analysis.

While these correlations are intriguing, the primary focus of this study was to investigate the combined influence of various factors on recovery. We believe that understanding the interplay of these variables, rather than focusing solely on individual correlations, offers a more comprehensive understanding of recovery dynamics. Consequently, in our manuscript, we continue to focus on explaining the results of the SLG. Table 4 serves as a reference for our readers to consider these additional insights.