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Impacts of COVID-19 on Public Transit Ridership

Final Report

by

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EXECUTIVE SUMMARY

The impacts of COVID-19 on public transit have been substantial. The public transit agencies are facing unprecedented challenges, including operator absenteeism, a sharp decline in ridership, new disinfection practices, and the maintenance of personal protective equipment (PPE) for the safety of operators and riders. Meanwhile, public transit is critical for essential workers to commute and for citizens to access food and medical services. These challenges will continue changing and impact public transit significantly.

In this paper, a national-wide study is conducted to investigate the impacts of COVID-19 on the public transit ridership in the top twenty metropolitan areas in the U.S. At first, COVID-19 composite index was developed to qualitatively measure the level of public fear toward COVID-19 in different metropolitan areas. After that, to analyze the impact of COVID-19 and some socioeconomic factors on transit ridership reduction during the COVID-19 pandemic, a random-effects panel data model was developed. In addition, correlation analysis was conducted to further analyze the impacts of the identified socioeconomic factors. According to the results of both analyses, it was found that the areas with higher median household income, a higher percentage of the population with a Bachelor's degree or higher, a higher employment rate, and a higher percentage of the Asian population are more likely to have more reductions in public transit ridership during the COVID-19 pandemic. On the other side, the areas with a higher percentage of the population in poverty, and a higher percentage of the Hispanic population are more likely to experience smaller reductions in public transit ridership. The findings of this study can help public transit agencies and local transportation planning organizations better understand the causes and patterns of changes in public transit ridership during the pandemic.

Chapter 1. Introduction

The widespread COVID-19 has led to profound impacts on our society, economy, and transportation systems. It has theatrically altered public travel behavior worldwide and posed a great challenge for public transportation operations worldwide.

As one of the most essential services, public transit provides people with mobility for accessing community resources, medical care, employment, and recreational opportunities. It is not only a choice of transportation mode but an essential mobility service for those who have no other choice. Note that, over 90% of public assistance recipients do not own a car and must rely on public transit (*FHWA, 2002*).

During the COVID-19 pandemic, public transit keeps our cities functioning by providing transportation services to essential workers in health care, emergency services, food services, and other sectors. It was reported that about 33% - 36% of the total 2.8 million public transit passengers are essential service workers such as grocery store employees, delivery people, first responders, and healthcare workers who still depend on access to public transit to get to work (*Mangan, 2020; Cooperman, 2020*).

It also acts as a major engine of economic stability and equity. During the COVID-19 pandemic, certain groups of people face special challenges. First, senior people have major challenges because they are at a higher risk of serious disease if infected with the coronavirus. They have been strongly advised to stay at home. They do not often drive or even have no car to drive. However, they still need food and possibly medication, and they may need to make routine yet lifesaving trips to, for instance, doctor appointments. Besides senior people, low-income people also rely on public transportation to reach free food distribution sites and supermarkets. Homeless people may need to access test sites and quarantine locations for the safety of themselves and their neighborhoods. It is in these moments that many human service organizations have been closed, and public transportation becomes an essential service for these special groups of people.

In summary, public transit is one of the essential services during the COVID-19 pandemic. It provides transportation services to healthcare workers and other professionals whose work is critical in fighting the COVID-19 pandemic. It also serves some special groups of transit-dependent people. It keeps our city running and is critical to the economy and social equity.

According to Transit Data collected from public transit agencies in April 2020, the ridership levels across all public transit modes have decreased by 73% in the United States, especially the light rail mode has been reduced by nearly 90% (*Transitapp, 2020; EBP, 2020*). The sharp decline in the number of passengers will affect the operation of public transit and tighten the funding sources. Meanwhile, public transit is critical for citizens to access essential services such as food or medical services and it will remain at the core of transport systems that keep people moving and keep our cities running. Therefore, understanding the impacts of COVID-19 on public transit ridership will be critical for transportation planning to make the right decisions for maintaining safe and effective public transit services under such special circumstances. Some previous studies have conducted regional-specific analyses of the impacts of COVID-19 on the ridership of a particular transit system (Hu and Chen, 2021; Wilbur et al., 2020; and Brough et al., 2020). A national-wide study is needed to investigate the impacts of COVID-19 in different metropolitan areas across the U.S. In addition, most existing studies simply used COVID-19 confirmed cases and (or) confirmed deaths as indexes in their analysis. A composite index that can better measure the level of public fear toward COVID-19 in an area or the level of public fear toward COVID-19 needs to be used for the model development. Furthermore, previous studies have found that the magnitude of impacts of COVID-19 varied across different socioeconomic groups (Hu and Chen, 2021; Wilbur et al., 2020; and Brough et al., 2020). Thus, the equity problem caused by COVID-19 needs to be further investigated based on nationwide data. To fill these gaps, this research is to investigate the impacts of COVID-19 on the public transit ridership in the top twenty metropolitan areas in the U.S. To this end, the following specific research objectives have been set up:

1) Develop a COVID-19 composite index that can quantitatively measure the level of public fear toward COVID-19 in an area.
2) Develop an advanced mathematical model to analyze the impacts of COVID-19 and some socioeconomic factors on transit ridership reduction during the COVID-19 pandemic.

This study is among the first research to use a COVID-19 composite index in modeling the impacts of COVID-19 on public transit ridership change. In this study, we collected and analyzed the public transit (bus and light rail) ridership data for the top twenty metropolitan areas in the United States. Through a comprehensive literature review, the reasons for transit ridership decline and the impacts of COVID-19 on different sociodemographic groups are discussed. After that, an panel data model was developed to identify the factors that affect the public transit ridership reduction during the COVID-19 pandemic. Finally, conclusions are provided.

Chapter 2. Literature Review

It is been over two years since the outbreak of COVID-19, and several studies have been conducted on the impact of COVID-19 on public transit ridership in different aspects. Based on the review of these existing studies, the following four topics are discussed in this chapter: 1) transit ridership decline and reasons, 2) impacts of COVID-19 on different sociodemographic groups, 3) methodology for analyzing the impact of COVID-19 on public transit ridership, 4) countermeasures on reducing the COVID-19 transmission risk in public transport, 5) public transit riders' perception and experience of safety and 6) countermeasures for maintaining effective public transit service during a pandemic.

2.1 Transit Ridership Decline and Reasons

Declines in transit ridership during the COVID-19 pandemic have been observed across the world (Transitapp, 2020; EBP, 2020; WMATA, 2020). For example, in Washington DC, Metrorail ridership declined by a maximum of 90%, and bus ridership declined at a maximum of 75%, subway ridership decreased by 77%, compared with the transit ridership in 2019 (WMATA, 2020). In Britain, the COVID-19 outbreak has led to a 90% drop in rail travel and 94% and 83% reductions in tube and bus journeys in London respectively (Carrington, 2020). Averagely, the COVID-19 pandemic has caused a 72.4% reduction in ridership for 95% of stations in Chicago (Hu and Chen, 2020). The impact of the pandemic was also felt by the Houston region, with a 40% decrease in public transportation due to the fear of the virus transmission (Rozen, 2021). An assessment conducted by the Air Alliance Houston, LINK Houston, and Texas Southern University found the transit vehicle miles traveled (VMT) decreased in several Texas counties. Compared to the January average, Harris County saw a 79% drop in VMT levels in April of 2020. Ahangari et al. (2020) conducted a compliance analysis between 2019 and monthly changes of 2020 by mode and type of services in Baltimore and nine other U.S. cities. They found in March, April, and May 2020, the ridership decreased in all ten selected cities in response to the stay-at-home orders which took effect in March. The level of ridership hit its lowest peak in April in all ten cities, which was 62-87% less than the 2019 levels. Various factors on both the demand side and supply side cause the sharp drop in transit ridership during the COVID-19 pandemic.

Demand-side reasons

On the demand side, first, the lockdown and stay-at-home orders abruptly cut trips in many cities (Wilbu et al., 2021). Second, during the pandemic, many businesses allow their employees to work at home and many schools provide virtual learning options to their students, which further reduced the demand for work-related trips. Unemployment was also found to be a factor impacting rail ridership reduction in April 2020 (Ahangari et al., 2020). Third, since public transit involves collectively moving a group of passengers in an enclosed space, it may increase the risk of COVID-19 transmission (Zheng et al., 2020). To minimize exposure to risky environments, travelers intensively avoid riding public transit. They shifted from public transit to passenger cars and other modes. This was also proven by Rozen's study, which shows that people switch to personal vehicles, carpooling, or ride-hailing services post-pandemic because health considerations, with nearly three-quarters concerned about cleanliness or catching an illness (2021). For example, in the early days of the pandemic, the fears of infection may have spurred car purchases in New York City and the car travel was quicker to recover than any form of public transit during the pandemic (Penney, 2021). Also, Capgemini Research Institute has conducted a survey of 11,000 consumers from 11 countries and found that 46% of respondents plan to use their car more frequently and make less use of public transport (Winkler, 2021). Furthermore, Teixeira and Lopes (2020) found that “there is some evidence of transit users shifting to the shared bike programs” in New York City.

Supply-side reasons

On the supply side, due to the social distancing directives and other safety protocols to prevent the spread of coronavirus, and public transit agencies have to reduce their service capacity. For example, to keep social distance, all public transit agencies reduced vehicle capacity from 25% to 75% to keep passengers at least 6 feet distance from each other. For example, Houston reduced 50% by tagging the other seats as unavailable (see Figure 6). New York, Washington DC, Phoenix, Minneapolis and Baltimore reduced 75% capacity; St. Louis reduced 25% capacity (MTA, 2020; WMATA, 2020; VMTS, 2020; Minneapolis Metro Transit, 2020; Maryland Transit Administration, 2020). In addition, during the pandemic, due to the insufficient transit workforce, the sharp drop in fare revenue, and the strengthening of cleaning procedures, many transit agencies reduced their service hours and routes, and keep essential functions only (DeWeese et al., 2020). For example, Los Angeles trimmed service by about 10% (Los Angeles County MTA, 2020). By mid-April 2020, King County Metro had made three rounds of service adjustments and was operating 27% fewer service trips than its typical weekday service (Switzer 2020). The reduced service caused longer waiting times at transit stations and more crowded buses/trains for some transit lines, which will cause further ridership reduction and more trip shifts from public transit to other modes.

Figure 1 Placards on Bus for Keeping Social Distancing
(Source: *METRO, 2020*)

Other factors

Some other unobserved factors like government policies and vaccination rates may also contribute to the change in the public transit ridership. For example, as COVID vaccination becomes widespread, there is a recovering trend in public transit ridership (George et al., 2021). In addition, mandatory mask orders and mask compliance rates may also affect the public transit ridership.

2.2 Impacts of COVID-19 on different sociodemographic groups

COVID-19 caused dramatic transit ridership drops in early 2020 after World Health Organization declared it a pandemic. Specifically, the impacts of COVID-19 on public transit are different among different sociodemographic groups due to the different abilities of different groups of individuals to adjust their travel behavior in the face of the challenges of pandemic and various changing policies (Brough et al., 2020). For example, women, people of color, low-paid workers, those without access to a car, people with disability, and those older than 50 years of age maintained greater levels of transit ridership during the pandemic (Kapatsila & Grise, 2021). Workers and members of the labor force with no teleworking options and no alternate means of transportation continued to rely on public transit following the onset of the pandemic. Whereas people who work in information, management, and technology-related positions are more likely to be able to work from home (Tan et al., 2020). Generally, high-income people have low intentions to use public transport in a pandemic situation (Javid et al., 2021).

In terms of the communities, Meredith-Karam et al. (2021) found dramatic ridership drops in various major cities while finding that many socioeconomically disadvantaged communities maintained greater levels of transit ridership during the pandemic, likely due to limited alternative travel options and the disproportionate likelihood of working in essential jobs which could not be conducted remotely. Another study conducted by Air Alliance Houston, LINK Houston, and Texas Southern University in Houston found that transit ridership in the Gulfton/Sharptown community, two predominantly minority and low-income communities, increased in October 2020. This data point coincides with the feedback they heard during the focus groups with residents of these two communities, and many said they never stopped using public transportation during the pandemic. Other focus areas and the METRO service area at -large continued to see below-average ridership after the break out of the pandemic. They also found that communities containing many essential workers continued to rely on public transportation for work and necessities.

Survey results indicate that the ridership of public transportation in Santiago was reduced by about 30% to 40% for low-income households, while for high-income households, the reduction of ridership was more than 70% (Tirachini and Cats, 2020). Several studies have found that areas with more lower-income, lower-educated, and people of color households had fewer declines in the ridership of public transit during the COVID-19 pandemic. Brough et al.(2020) found that at the initial stage of the pandemic in King County, Washington State, high-income residents are disproportionately switching from public transportation to cars. However, over time, the differences in the travel behavior of different socio-economic groups have reduced. It was also found that the travel reduction is less among less-educated and lower-income individuals even taking into account the model substitution and the reduction of differentiated public transportation services. Wilbur et al. (2020) found that the high-income areas of Nashville City showed a reduced transit ridership of more than 19% compared to the low-income areas in that city. Hu and Chen (2020) found that the ridership of the “L” train system in Chicago has reduced more in regions with more commercial lands and a higher proportion of white people, educated, and high-income people, while regions with more employment in trade, transportation, and utility sectors or with more COVID-19 cases/deaths show smaller reductions in ridership. A review of the studies focusing on specific metropolitan areas by Sullivan (2021) found that ridership declined more in zones with a greater amount of commercial land and a higher percentage of high-come individuals and declined less in a zone with a greater number of essential jobs and the declines were largest during the rush hours.

These previous studies have discussed the underlying causes of the socio-economic gap in the changes in public transit ridership. First, low-income and historically marginalized groups tend to be more reliant on public transportation. These riders have fewer options than other commuters (Sullivan, 2021). Pucher and Renne (2003) found that minorities and low-income households account for 63% of transit riders in the United States. LINK Houston's 2018 Equity Transit Report shows that about 33% of transit riders live in households in poverty. Second, during the pandemic, essential workers must go to the workplace irrespective of the stay-at-home order. A recent analysis found that essential workers account for about 36% of total transit passengers in the United States (TransitCenter, 2020). Most of the essential workers are non-white and have low incomes (Hu and Chen, 2020). In addition, the less-educated and lower-income people are relatively incapable of working remotely. The home conditions of the less-educated and lower-income groups are generally less hospitable for work or study at home due to a “lack of adequate internet access, space constraints, and limited access to outdoor areas” (Brough et al., 2020).

2.3 Methodologies for analyzing the impact of COVID-19 on public transit ridership

Different types of statistical methods have been used to analyze the impact of COVID-19 on public transit ridership. First, the traditional correlation analysis method has been used for identifying the factors that are strongly correlated with the ridership decline of public transit during the pandemic (Wilbur et al., 2020). Correlation analysis is a good method for quantifying the strength of the linear relationship between a pair of variables. However, it cannot account for the collective effects of multiple variables. To address this problem, many studies have used multivariable linear regression in transit ridership analysis. Ahangari et al. (2020), Brough et al.(2020), and Liu et al. (2020) used the ordinary least squares (OLS) regression method to analyze the factors that are affecting transit ridership changes during the pandemic. The limitation of the traditional regression model is that it assumes that all observations are independently and normally distributed, which may not always be true. Therefore, advanced methods have been used. For example, Hu et al. (2020) used the partial least squares regression to model the impacts of various factors such as land use, COVID-19 virus-related, socioeconomic, and transit service on the ridership reduction. The partial least squares regression is good for addressing the multicollinearity problem in the regression model. However, there are some gaps in the existing studies.

- First, in order to assess the impact of COVID-19, a quantitative indicator for measuring the level of public fear toward COVID-19 in an area needs to be developed first. In general, two COVID-19 indexes have been commonly used: confirmed cases and confirmed deaths. Some studies simply use one of these indexes or use both indexes in their models. Since the number of confirmed cases or deaths is highly related to the type and population size of an area (a big city tends to have more cases than a small town), using the absolute number of cases or deaths will affect the model transferability. In addition, since these two indexes are highly correlated, simply including both two indexes in the model would undermine the modeling results. Liu et al. (2021) have used the Google search trend index for the keyword "Coronavirus" to measure public awareness and concern about COVID-19. This measure may be able to reflect the level of public awareness at the beginning of the pandemic. However, as time goes by, and people become more familiar with COVID-19 and its information resources, the number of searches will decrease. Therefore, a composite index that can better measure the level of public fear toward COVID-19 in an area needs to be developed.

- Second, in most of the public transit studies, the transit ridership data were collected from different metropolitan areas during different periods. For example, in Liu et al. (2020), daily transit ridership data were collected from 113 county-level transit systems in 63 metro areas from February 15^{th} to May 17^{th}, 2020. The observations from the same area are very likely to be correlated. Therefore, the assumption of the traditional regression model that all observations are independently distributed may not be held. To address this problem, the panel data modeling approach can be used to model the cross-sectional observations in different periods.

To fill these two identified gaps, in this study, a composite index was developed to measure the level of public fear toward COVID-19 in an area and a random-effects panel data model was developed to analyze the impacts of COVID-19 and some socioeconomic factors on the ridership reduction during the pandemic.

2.4 Countermeasures for reducing the COVID-19 transmission in public transport

Various countermeasures were recommended to reduce the transmission of COVID-19 in public transport.

Social distancing

First, maintaining "social distancing" is effective in reducing the transmission of COVID-19 in public transport. According to the information from the Centers for Disease Control and Prevention (CDC), people in close contact with each other (within about 6 feet) consider one of the main ways to spread the coronavirus.

A study conducted by Kamga and Eickemeyer (2021) comprehensively reviewed the literature to explore social distancing measures deployed by the public transportation industry in the United States and Canada during the COVID-19 pandemic. The authors reviewed available evidence including news articles, virtual presentations, and agencies' websites beginning in March 2020 to assess what specific measures public transit operators have applied to implement physical separation while riding and in all facilities. The deployed interventions were grouped into two separate categories as infrastructure and operations. In several states, official instructions were issued for social distancing. The public transport operators were charged with providing a social distance of six feet between passengers on their property and physical infrastructure. For physical distancing, operational changes were needed, such as adding train cars to provide opportunities for physical distance on the train. Examples of such measures in this research include taping off every other seat on buses, increasing the total length of trains by adding cars, separating bus drivers from passengers with plastic sheeting, rear door boarding, and others.

An online survey conducted by Kapatsila and Grise in 2020 in Edmonton, Canada shows that riders feel safe using public transit when they are informed about the measures Edmonton Transit Service is taking to ensure physical distancing and meet riders' health and safety concerns (Kapatsila and Grise, 2021).

Another study was conducted by Bilde et al. (2021) to determine whether the social distancing goals set by the public health authorities can be reasonably met within the existing infrastructure or with minor alterations in Copenhagen, Denmark, where public transport is a critical service as residents do not own cars and car travel is not practical in the city due to narrow roads and lack of parking. In response to COVID-19, Danish public health authorities have established a minimum 1 m social distancing policy in public spaces. The physical flows of passengers inside the stations have been simulated using the commercial software Bentley Legion with small, medium, and large traffic flows. The simulations with Bentley Legion offer a complete analysis of each station. They have consulted several international studies to determine specific parameters such as average passenger space requirements and walking speed distributions. Three stations have been chosen from the M1/M2 routes to represent three levels of station size, where passenger counts measure station size. The selected stations were Nerroport (Large), Forum (Medium), and Oresund (Small). The results showed that COVID-19 does not create any significant passenger flow issues with most stations. However, for a few of the highest-demand stations, those serving as intermodal hubs show difficulties in achieving the desired social distancing measures because they do not have corridors and escalators distributed correctly according to the pedestrian flow.

To keep social distancing, most public transit agencies reduced vehicle capacity limitations from 25% to 75% to keep passengers at least 6 feet distance from each other. For example, Houston Metro reduced the bus capacity by 50% by tagging the other seats as unavailable (METRO, 2020). Adeke et al. (2021) investigated the transmissibility of COVID-19 among passengers using public transport modes in Makurdi metropolis, Nigeria. The study assesses the impacts of layout and occupancy of public transport modes during the COVID era. The mode occupancy was divided into three major scenarios, namely: 1) normal, which was the ideal capacity of the mode; 2) above normal was the nonstandard capacity which in most cases accommodated higher than the ideal situation and 3) below normal which was half the ideal capacity recommended by authorities and the COVID-19 guidelines for public transport systems. The findings showed that the optimum capacity of the minibus, taxies, tricycles, and motorcycles used in Makurdi metropolis were at 8, 3, 2, and 1, respectively. The analysis revealed that public transport modes operated safely when all modes carry capacities below normal at 50% full.

Hygiene Measures

Second, hygiene measures are proven effective in preventing virus transmission. During the COVID-19 pandemic, all public transit agencies increased cleaning and disinfecting for both bus and light rail facilities and terminals daily, especially for high-touch surfaces like doors, handrails, and fare vending machines. The frequencies of cleaning and disinfecting were increased during peak hours. For example, New York disinfected stations twice every day and piloted the first-ever ultraviolet light, electrostatic sprayers, antimicrobial biostats, and the new innovative air filters for disinfecting vehicles (*MTA, 2020*); Los Angeles cleaned the vehicles the same as hospital-grade daily; Chicago and Miami instituted the disinfection of vehicles and high-touch surfaces multiple times per day; Boston cleaned all high-contact areas at subway stations six times per day (MBTA, 2020). In addition, all public transit agencies provided hand sanitizer (at least 70% alcohol) and disinfectant wipes for operators. For example, St. Louis provided PPE including gloves and masks (*Metro St. Louis, 2020*). It was reported that New York distributed 240,000 masks and 3.2 million gloves to its workforce in March (*MTA, 2020*). Boston deployed hand sanitizing dispensers, disinfectant wipes, and cleaning sprays at facilities and stations throughout the system for operators and passengers (*MBTA, 2020*).

Research shows that hygiene measures, both personal hygiene measures and onboard hygiene measures could reduce COVID-19 transmission. Personal hygiene measures include wearing masks and other personal protective measures; onboard hygiene measures include ventilation such as using onboard fans and opening various windows, implementing cleaning and sanitation practices, etc. Kapatsila and Grise (2021) found riders place a high value on cleaning and sanitation practices to feel safe using public transit in Edmonton during the COVID-19 pandemic. Lucchesi et al. (2022) found wearing masks and vehicle hygiene were perceived as safer countermeasures to make users feel safe while riding in public transport.

COVID-19 Detection and Tracking

Third, timely detection and tracking COVID-19 infection cases are critical for preventing the spread of coronavirus. To this end, the following countermeasures have been taken by the public transit agencies

- *COVID-19 detection*

All public transit agencies checked their employee's temperatures before working every day. If an employee with a temperature greater than 100.4 °F, they are not allowed to work and are instructed to seek medical guidance.

- *COVID-19 tracking*

Even though all possible safety measures were taken to keep the buses clean and prevent the spread of infection, all public transit agencies anticipated the possibility of having passengers with COVID-19 and established a system to efficiently track buses, drivers and other passengers who might have been in contact with the infected passengers. If COVID-19 passenger(s) are suspected, the bus and/or driver must be quarantined, then other co-passengers suspected to have been present around the COVID-19 infected passenger(s) must be informed to self-isolate and health authorities must be informed to initiate other procedures. For example, Los Angeles, Washington DC, and Atlanta created an online chart with confirmed cases of COVID-19 among employees and contractors (*WMATA, 2020; MARTA, 2020*). METRO Houston daily updated the COVID-19 tracking results of the operators on the website, which listed the specific dates the bus operator last worked, during that time, and which routes the operator drove. In addition, METRO also worked with public health officials so they can identify and notify passengers, and any employees who may have been in close contact with the reported operators (*METRO, 2020*).

2.5 Public Transit Riders' Perception and Experience of Safety

Public transit riders' perception and experience of safety greatly affect whether they will feel safe using public transit in the post-pandemic era.

Javid et al. (2021) conducted a study to identify the travelers' attitudes and preferences toward using public transport during COVID-19 pandemic. They prepared a comprehensive questionnaire and conducted a survey during October and November 2020, when the lockdown had been lifted in Lahore, Pakistan. They found that the travelers' better awareness, responsibility, and trust in using public transport may strongly influence their preferences towards public transport during a pandemic situation. On how to increase the users' preferences to ride public transport, Lucchesi et al. (2022) conducted an online survey with public transportation users in a metropolitan area in southern Brazil and found that limiting the number of people in the vehicles, wearing masks, and vehicle hygiene was perceived as the safer countermeasures to make users feel safe while riding in public transport. They also identified the barriers preventing the users' migration and potential solutions using Hybrid Choice Models (HCMs) to increase users' perception of safety and public transportation quality. The barriers include riders' concerns about the high number of users in the vehicles, crowded vehicles, crowded stops, and stations.

To improve travelers' perception and experience of riding public transit, social media should be accessible for riders to understand the strategies. Diaz et al. (2021) explored the accessibility and usability information of the physical and communication measures taken by the 25 most populous Canadian city transit agencies and how transit agencies in Canada used social media to communicate their efforts to the public.

In terms of the type of social media, most larger agencies used Twitter platforms as most agencies employed tweets, including graphics; very few used videos and animations to communicate important information to the public. The findings will help policymakers and transit planners with extensive information about the initial response of transit agencies in Canada and other countries in the world to maintain operation during critical times and help develop more effective strategies to deal with such future challenges. All this research help build transit riders' preference for public transport and help reduce passenger evasion and migration to more unsustainable transport modes.

2.6 Countermeasures for Maintaining Effective Public Transit Service During a Pandemic

As an essential lifeline, all the transit agencies remain committed to serving the public and continue to meet the needs of transit-dependent riders during the COVID-19 pandemic. According to the information collected from the studied public transit agencies' official websites, the following are the main countermeasures taken to maintain effective public transit service during the pandemic.

Change of Service

Due to the ridership dropping, and the social distancing directives and other safety protocols to prevent the spread of coronavirus, and public transit agencies must scale back service and keep essential functions only.

- *Reduce the scale of services*

All public transit agencies reduced service hours and routes to address ridership dropping and added more buses to the routes with higher ridership at peak hours. The service hours and routes were reduced by applying the weekend schedule (a Saturday or Sunday schedule) to weekdays schedule. For example, Los Angeles trimmed service by about 10%.

- *Increase service for some essential routes*

More buses have been added to the essential route during the peak hour. For example, Houston and Boston added routes to better accommodate the mobility needs of health care workers and emergency responders; Dallas-Fort Worth-Arlington added more buses to the routes with higher ridership at peak hours (*METRO, 2020; MBTA, 2020; DART, 2020*). SFMTA has increased its transit service frequency, and added select routes, and extended some current routes to continue to support essential trips (*SFMTA, 2020*).

Responsive Dispatcher and Flexible Stops

Bus drivers will stay in frequent contact with the public transit control center, alerting them if they reach capacity. Transit agencies can monitor capacity daily through automatic passenger counts and assessments from inspectors on the street, which gives them a holistic view of what is happening on the street so they can make adjustments as resources become available. In addition, the bus operator has the right to make decisions at the stop. If a bus becomes too crowded, operators can skip stops. For example, Chicago Transit Authority announced bus operators have the authority to temporarily run as “drop-off only” and bypass certain bus stops if their bus is becoming crowded (*CTA, 2020*).

Switch of Operators from Light Rail to Bus

Aa we mentioned before, many light rails have been suspended and the ridership of light rail dropped more than the bus. To fully use all the available resources, it is feasible that the light rail operators can switch to bus operators during the pandemic. Since April 1st, SFMTA announced that all Muni Metro Light Rail routes are temporarily being served by Metro buses. Because Muni drivers are cross-trained to handle different vehicle types, they have some flexibility in moving light rail operators to the bus shuttles. It also allowed them to simplify their operations and refocus cleaning staff from largely empty light rail stations to other critical areas, such as bus yards, field operations, and other facilities that are currently seeing more activity (*SFMTA, 2020*).

Paratransit

During the pandemic, for essential workers who rely on public transit, but because of the reduced transit service, these workers are no longer able to reliably get to or from work. To address this concern, several public transit agencies launched different Paratransit programs. Pinellas Suncoast Transit Authority (PSTA), one of the major transit agencies in Tampa-St. Petersburg metropolitan area, works to get the essential workers rides to or from work curb to curb on either Uber, United Taxi, or Care Ride (*PSTA, 2020*). Minneapolis Metro Transit launched Metro Mobility program which provides free door-to-door service from home to work and work to home for any person who works at a healthcare facility, 24 hours a day, 7 days a week (*Minneapolis Metro Transit, 2020*). San Francisco Municipal Transportation Agency (SFMTA) announced the Essential Trip Card to help older adults and people with disabilities take and pay for essential trips in taxis during COVID-19 pandemic, SFMTA also launched Shop-a-Round, a convenient, low-cost shuttle or subsidized taxi ride to serve registered seniors and people with disabilities personalized assistance and a rider to/from the grocery store (*SFMTA, 2020*). Massachusetts Bay Transportation Authority (MBTA, 2020) announced the RIDE paratransit service temporarily allows customers to book trips for their personal care attendants (PCAs) to best support their ADA-eligible customers during the COVID-19 situation (*MBTA, 2020*). King County Metro Transit is offering essential workers who have been impacted by recent transit cuts the opportunity to form temporary Vanpools with reduced ridership requirements for the COVID-19 response and recovery efforts. Typically Vanpools need five or more riders to commute. These temporary reduced-ridership Vanpool groups allow for social distancing and provide essential workers rideshare options where other transit options are unavailable or unfeasible.

Summary

The impact of COVID-19 on public transit is significant. To deal with the COVID-19 pandemic, all the public transit agencies have taken some countermeasures for preventing the spread of coronavirus by following the guidelines from CDC and APTA. These countermeasures include Social distancing, hygiene Measures, and COVID-19 detection, and tracking.

Maintaining effective public transit service is also important during the COVID-19 pandemic. To this end, different types of countermeasures have been taken to continue serving the public and to meet the mobility needs of essential workers and other transit-dependent riders. These countermeasures include change of service, responsive dispatcher and flexible stops, paratransit, and switch of operators from light rail to bus. All these solutions can help public transit maintain quality service during the pandemic which can be prepared for the future unknown outbreak.

Chapter 3. Data Description

In this study, we investigated the change in public transit ridership for 1 year from February 1st, 2020 to January 31st, 2021 since the World Health Organization (WHO) issued a global health emergency on January 30th, 2020. Three different types of data were collected: 1) COVID-19 cases and deaths data during the study time period, 2) public transit ridership data from February 2019 to January 2021, and 3) sociodemographic data of the selected metropolitan areas during the study time period. The COVID-19 case and death data were collected from USA FACTS official website (USAFACTS, 2020). The ridership data are the monthly public transit ridership data collected by the National Transit Database (NTD) from the Federal Transit Administration (FTA) (NTD, 2020). The sociodemographic data of the studied metropolitan areas was retrieved from the American Community Survey (ACS) 1-year estimates data profile (United States Census Bureau, 2019).

The COVID-19 case and deaths data included all COVID-19 daily confirmed cases by counties and by states. Note that, since the COVID-19 data is county-based instead of metropolitan-based, in this study, county-based cases and deaths within each metropolitan area were aggregated to derive the metropolitan-based cases and deaths. For the public transit ridership data, we focus on the impacts of COVID-19 on the bus and light rail transit modes in the study areas. Different types of buses were considered, including motorbus (MB), Commuter Bus (CB), and Bus Rapid Transit (RB). The ridership is reported as the number of unlinked passenger trips, which are defined as the number of passengers who board public transit vehicles. As we mentioned before, the data was collected for the major transit agencies in the top twenty metropolitan areas based on their population. These top twenty metropolitan areas along with the major public transit agencies in these areas are presented in Table 1.

Table 1 Summary of Studied Metropolitan Areas

	Metropolitan Area	Population	Major Public Transit Agenci
1	New York-Newark, NY-NJ-CT	19,216,182	Metropolitan Transportation Authority
2	Los Angeles-Long Beach-Anaheim, CA	13,214,799	Los Angeles County Metropolitan Transportation Authority
3	Chicago, IL-IN Chicago	9,457,867	Chicago Transit Authority
4	Miami, FL	6,166,488	Miami-Dade Transit
5	Philadelphia, PA-NJ-DE-MD	6,102,434	Southeastern Pennsylvania Transportation Authority
6	Dallas-Fort Worth-Arlington, TX	7,573,136	Dallas Area Rapid Transit; Trinity Metro
7	Houston, TX	7,066,140	Metropolitan Transit Authority of Harris County
8	Washington, DC-VA-MD	6,280,697	Washington Metropolitan Area Transit Authority
9	Atlanta, GA	6,018,744	Metropolitan Atlanta Rapid Transit Authority
10	Boston, MA-NH-RI	4,873,019	Massachusetts Bay Transportation Authority
11	Detroit, MI	4,319,629	The Detroit Department of Transportation
12	Phoenix-Mesa, AZ	4,948,203	Valley Metro Transit System
13	San Francisco-Oakland, CA	4,731,803	San Francisco Municipal Transportation Agency
14	Seattle, WA	3,979,845	King County Metro; Sound Transit
15	San Diego, CA	3,338,330	San Diego Metropolitan Trans System
16	Minneapolis-St. Paul, MN-WI	3,640,043	Metro Transit
17	Tampa-St. Petersburg, FL	3,194,831	Pinellas Suncoast Transit Authority
18	Denver-Aurora, CO	2,967,239	Regional Transportation Distri
19	Baltimore, MD	2,800,053	Maryland Transit Administrati
20	St. Louis, MO-IL	2,801,423	Metropolitan Saint Louis Tran Agency

The dependent and independent variables used in this study were presented in Table 2, and detailed explanations of these variables are provided in the following sections.

3.1 Dependent variables

In this study, the dependent variable is Year-on-Year (YoY) monthly ridership reduction rate, which compares the ridership for a given month during the study period with the ridership in the same month of previous years. Take the first month, February 2020, as an example, the YoY ridership reduction rate of February 2020 can be expressed mathematically as follows:

$$
\begin{aligned}
&YOY\ Reduction\ Rate\ of\ Feb.2020 \\
&= \frac{Monthly\ ridership\ of\ Feb.2019 - Monthly\ ridershipo\ of\ Feb.2020}{Monthly\ ridership\ of\ Feb.2019}
\end{aligned}
$$

The derived YoY reduction rates of transit ridership of different metropolitan areas are presented in **Figure 2.** As shown in this figure, all twenty public transit agencies have experienced a sudden ridership drop since March 2020 and then reached a stable level. It can be seen that all these areas suffered a 40%-85% ridership reduction from March 2020 to April 2020. Among them, San Francisco-Oakland and Washington are the top two metropolitan areas with the highest ridership reduction rates. The ridership of New York has the sharpest decline at the beginning of the pandemic and it recovered a little bit and remain at around 60% YoY reduction rate during the rest of the time. Tampa-St. Petersburg has the relatively lowest ridership reduction rate at the beginning of the pandemic, but its reduction rate jumped to 70% in January 2021. From Figure 2, it can be seen that overall the transit ridership for all areas has been reduced significantly. However, the reduction rate various by time and area. In this study, we will use mathematical methods to investigate the impacts of COVID-19 on the ridership changes and other contributing factors to the ridership reduction in different metropolitan areas.

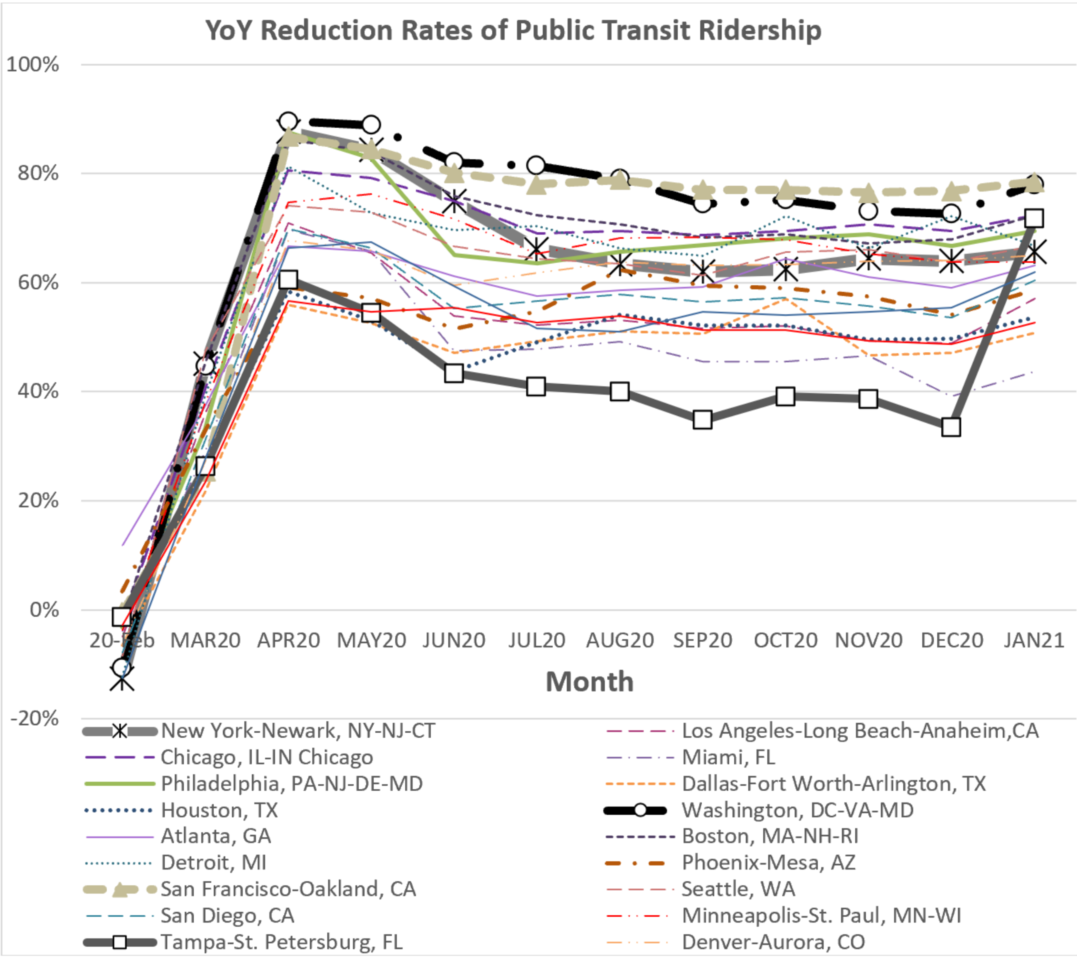

Figure 2 YoY reduction rates of transit ridership of the selected metropolitan areas

3.2 Independent Variables

Two types of independent variables are considered in this study: COVID-19 related factors and sociodemographic factors. The definitions of all the independent variables considered by this study are present in Table 2.

Table 2 Dependent and Independent Variables

Variables	**Description**
Dependent Variable	
YoYMRRR	Year-on-Year (YoY) monthly ridership reduction rate
Independent Variables	
CI	COVID-19 Composite Index
Percentage of Poverty	Percentage of population under poverty thresholds
MHI	Median Household Income
Percentage of H.S. degree or higher	Percentage of population with High Schoo degree or higher
Percentage of Bachelor's degree or higher	Percentage of population with Bachelor's degree or higher
Percentage of Non-English Speaking	Percentage of population who are Non-English Speaking
Percentage of Foreign-Born	Percentage of the population born in a forei country
Percentage of Households No Vehicl	Percentage of households without a vehicl
Percentage of Taking Public Transit to Work	Percentage of the population takes public transit to work
Employment Rate	Percentage of the population employed
Percentage of Hispanic	Percentage of the Hispanic population
Percentage of White	Percentage of the White population
Percentage of Black	Percentage of the Black population
Percentage of Asian	Percentage of the Asian population

COVID-19 Composite index

To analyze the impacts of COVID-19, the level of public fear toward COVID-19 in a particular area need to be quantitatively measured at first. In the field of stock market prediction, a CI, also known as the global fear index, has been used in analyzing how many distortions in the market can be attributed to the pandemic (Khan et al., 2020). Salisu and Akanni (2020) also constructed a global fear index (GFI) for the COVID-19 pandemic to predict stock returns. Since the CI could provide a measure of public perceptions toward the pandemic, the COVID-19 CI proposed by Salisu and Akanni (2020) is used as an independent variable for measuring the level of public fear toward

COVID-19 of the selected metropolitan areas in this study. Specifically, the CI for a metropolitan area *i* for a given day *t* can be developed by following three steps:

(i) Reported Cases Index (RCI):

$$RCI_t = \left(\frac{c_{i,t}}{c_{i,t}+c_{i,t-14}}\right) \times 100 \tag{1}$$

Where $c_{i,t}$ is the new confirmed cases at the current day *t* for the metropolitan area *i*; $c_{i,t-14}$ is the new confirmed cases at 14 days ago for the metropolitan area *i*. Because COVID-19 symptoms may appear 2-14 days after exposure to the virus (Centers for Disease Control and Prevention, 2021), this index measures the degree of deviation between the expected cases of reported cases in the next 14 days and the current reported cases. According to Equation 1, this index is in the range of 0 to 100, with the highest value representing the highest level of fear toward the pandemic, and the level of fear decreases as the index approaches 0 (Salisu and Akanni, 2020). Note that, if there are no changes during the past 14 days, this index will be 50. Similarly, the index for the reported death can also be derived as follows.

(ii) Reported Death Index (RDI):

$$RDI_t = \left(\frac{d_{i,t}}{d_{i,t}+d_{i,t-14}}\right) \times 100 \tag{2}$$

Where $d_{i,t}$ is the newly reported deaths at day *t* for the metropolitan area *i*; $d_{i,t-14}$ is the reported deaths at 14 days ago for the metropolitan area *i* . After that, by combining the calculated RCI and RDI, the COVID-19 Composite Index (CI) can be derived as follows

(iii) Composite Index (CI)

$$CI_t = [0.5(RCI_t + RDI_t)] \tag{3}$$

For each metropolitan area, the daily CI is calculated. Since the ridership data is monthly based, the daily CI was aggregated to derive the monthly average CI for each metropolitan area. The final CI results for each metropolitan area were presented in Table 3.

Sociodemographic factors

The sociodemographic factors are area-based, that is to say, these factors vary with different metropolitan areas and remain the same within different periods. To find the factors affecting transit ridership, sociodemographic data related to the income, poverty, and education levels, and the racial/ethnic composition of each metropolitan area was obtained from the American Community Survey (ACS) 1-year estimates data profile (United States Census Bureau, 2019). These data were presented in Table 4.

Table 3 Average Monthly CI of the Studied Metropolitan Areas

Metropolitan Areas	**20-Feb**	**MAR20**	**APR20**	**MAY20**	**JUN20**	**JUL20**	**AUG20**	**SEP20**	**OCT20**	**NOV20**	**DEC20**	**JAN21**
Atlanta, GA	0.00	36.21	60.95	49.57	48.61	58.76	48.44	43.72	49.92	50.18	56.81	53.76
Baltimore, MD	0.00	15.96	69.64	50.64	43.44	50.54	48.99	47.29	53.18	61.34	53.46	49.04
Boston, MA-NH-RI	0.00	34.55	75.46	38.32	38.36	49.70	46.76	54.08	57.98	55.66	48.49	56.43
Chicago, IL-IN	0.00	44.65	69.97	49.33	39.23	48.38	50.98	49.16	57.95	61.78	47.60	45.49
Dallas-Fort Worth-Arlington, TX	0.00	35.13	59.74	52.58	55.67	59.17	46.65	45.75	53.86	57.11	49.20	57.92
Denver-Aurora, CO	0.00	18.79	66.53	46.24	35.77	44.17	37.30	51.20	56.06	62.49	44.72	43.77
Detroit, MI	0.00	41.83	59.41	36.57	43.60	52.71	48.52	45.83	49.23	50.02	38.75	40.35
Houston, TX	0.00	19.18	62.90	47.57	64.22	59.47	48.03	41.64	45.92	54.04	50.15	60.45
Los Angeles-Long Beach-Anaheim,	0.00	40.61	69.96	51.28	52.59	52.35	45.89	44.70	49.87	58.81	61.03	52.76
Miami, FL	0.00	25.22	63.08	45.12	60.05	60.27	43.83	40.70	50.18	56.46	52.22	52.27
Minneapolis-St. Paul, MN-WI	0.00	12.37	65.91	59.85	41.35	45.64	51.85	48.23	52.67	56.65	46.97	43.95
New York-Newark, NY-NJ-CT	0.00	60.84	60.82	33.93	39.62	43.97	42.00	51.73	57.26	62.06	56.81	54.65
Philadelphia, PA-NJ-DE-MD	0.00	28.63	71.10	46.14	40.91	46.90	44.65	52.67	54.59	60.94	55.72	47.50
Phoenix-Mesa, AZ	0.00	19.14	61.61	52.17	61.53	56.23	35.28	42.89	49.97	56.41	44.20	58.83
San Diego, CA	0.00	15.97	56.72	43.35	44.84	42.47	34.82	41.85	43.47	40.19	52.58	46.45
San Francisco-Oakland, CA	0.00	32.75	56.74	45.65	49.96	52.74	49.68	46.04	47.95	53.66	57.55	52.83
Seattle, WA	3.45	84.06	49.95	39.88	51.84	48.39	48.01	31.72	44.29	40.79	22.49	36.50
St. Louis, MO-IL	0.00	19.30	62.03	48.15	41.61	53.52	49.33	49.54	50.47	58.85	45.35	48.95
Tampa-St. Petersburg, FL	0.00	22.40	43.51	52.17	63.76	54.81	44.53	43.29	48.77	55.34	53.49	52.06
Washington, DC-VA-MD	0.00	28.40	75.97	50.70	39.77	43.61	51.80	49.16	48.83	60.07	55.17	52.74

Table 4 Sociodemographic Data for the Study Metropolitan Areas

	Percentage of Poverty	Median Household Income	Percentage of Bachelor's degree or higher	Percentage of Non-English Speaking	Percentage of Foreign Born	Employment Rate	Percentage of Hispanic	Percentage of white	Percentage of Black	Percentage of Asian
New York-Newark, NY-NJ-CT	11.6%	83160	41.8%	40.0%	29.7%	65.2%	24.6%	46.2%	15.6%	11.3%
Los Angeles-Long Beach-Anaheim,CA	12.4%	77774	35.5%	54.4%	32.9%	65.5%	45.2%	29.8%	6.3%	16.0%
Chicago, IL-IN Chicago	10.6%	75379	39.2%	29.4%	17.6%	66.8%	22.3%	52.9%	16.3%	6.5%
Miami, FL	13.5%	60141	33.1%	55.1%	41.6%	63.6%	45.3%	30.4%	20.2%	2.4%
Philadelphia, PA-NJ-DE-MD	11.8%	74533	39.0%	16.3%	10.9%	65.6%	9.5%	61.8%	20.4%	6.0%
Dallas-Fort Worth-Arlington, TX	10.5%	72265	36.3%	32.2%	19.2%	68.8%	28.9%	46.7%	15.4%	6.7%
Houston, TX	12.9%	69193	33.3%	40.1%	23.4%	66.5%	37.3%	36.3%	16.9%	7.8%
Washington, DC-VA-MD	7.5%	105659	51.4%	29.6%	22.9%	71.5%	15.8%	45.4%	24.8%	10.2%
Atlanta, GA	10.5%	71742	39.9%	18.6%	14.2%	67.0%	10.8%	47.2%	33.4%	5.8%
Boston, MA-NH-RI	8.6%	94430	49.3%	25.2%	19.2%	69.5%	11.2%	70.4%	7.6%	7.9%
Detroit, MI	12.6%	63474	32.4%	14.2%	10.3%	63.1%	4.4%	66.7%	22.2%	4.3%
Phoenix-Mesa, AZ	12.1%	67896	32.2%	26.5%	14.3%	63.4%	31.0%	57.3%	5.1%	3.8%
San Francisco-Oakland, CA	8.2%	114696	51.4%	41.3%	30.9%	67.8%	21.9%	40.3%	6.9%	26.0%
Seattle, WA	7.8%	94027	44.1%	24.8%	19.7%	69.3%	10.1%	64.8%	5.6%	13.4%
San Diego, CA	10.3%	83985	39.9%	36.7%	22.8%	66.7%	33.9%	46.1%	4.6%	11.8%
Minneapolis-St. Paul, MN-WI	8.2%	83698	43.2%	14.9%	10.6%	71.6%	5.9%	76.0%	8.6%	6.7%
Tampa-St. Petersburg, FL	12.4%	57906	31.6%	22.6%	14.4%	60.3%	19.4%	63.0%	11.5%	3.5%
Denver-Aurora, CO	7.9%	85641	45.8%	20.2%	11.9%	71.5%	23.1%	64.7%	5.5%	4.3%
Baltimore, MD	9.4%	83160	41.9%	12.8%	10.3%	66.8%	5.9%	56.6%	28.8%	5.7%
St. Louis, MO-IL	9.9%	66417	35.8%	6.7%	4.8%	65.3%	3.0%	73.8%	18.1%	2.6%

Chapter 4. Methodology and Results

In this chapter, the methods used for data analysis are presented. First, a panel data model was developed to identify the factors that affect the public transit ridership reduction during the COVID-19 pandemic. After that, correlation analysis was conducted to further analyze the impacts of the identified socioeconomic factors.

4.1 Random Effects Panel Data Model

As we mentioned in the literature review part, in this study, the panel data modeling method is used for analyzing the impacts of COVID-19 on the transit ridership reduction rate and the impacts of other socioeconomic factors.

Panel data refers to observations of the same cross-sectional units observed at multiple time points. A panel-data observation X_{it} has two dimensions: $i = 1 \cdots N$ denotes the cross-sectional unit and $t = 1 \cdots T$ denotes the time period of the observation. In this study, the data consist of information collected from 20 big metropolitan areas during 12 months. Thus, it is the panel data with 20 cross-sectional units observed during 12 time periods ($N = 20$ and $T = 12$). In general, the panel data model can be expressed mathematically as follows (Green, 2000):

$$y_{it} = \alpha_i + \beta' X_{it} + \varepsilon_{it} \tag{4}$$

Where y_{it} is the dependent variable, i.e. YoY ridership reduction rate for the metropolitan area *i* ($i = 1 \cdots 20$) during the month *t* ($t = 1 \cdots 12$); X_{it} is the vector of independent variables as listed in Table 2; In the panel data model, there are two types of independent variables: 1) the individual-specific variables which are specific to the individual metropolitan area *i* and to be constant over time (during the different months), such as the sociodemographic variables listed in Table 2; and 2) time-variant variables which will change over time, such as the COVID-19 Composite Index; α_i is the individual effect which is specific to the individual metropolitan area *i* and to be constant over time; ε_{it} is the error term and β are the coefficient vectors for X_{it} .

In general, they are two types of panel data models: the fixed-effects model and the random-effects model. The random-effects model assumes that the individual-specific effects α_i are distributed independently of the independent variables while the fixed effects model allows α_i being correlated with the independent variables. In the random-effects model, α_i is included as a part of the error term, and in the fixed effects model, α_i is included as an individual specific intercept for the metropolitan area *i*. The fixed-effects model has the advantage of not requiring α_i to be independent with X_{it}, which is often difficult to verify. However, the standard fixed-effects model cannot identify the effects of any individual-specific variables because it requires the within-group variation for model estimation (Qi et al., 2007). The Hausman test can be used to choose between a fixed-effect model or a random-effect model(Green, 2000). The null hypothesis is that random-effects is the favored model and the alternate hypothesis is that fixed-effects is the favored model. In this study, the p-value of the Hausman test is 0.5526. Since it is greater than the 5% significant level, the null hypothesis cannot be rejected, which indicates that the random-effects model should be selected.

From the independent variables that list in Table 2, it can be seen that some of the sociodemographic factors may be highly be correlated. For example, the areas with a high percentage of poverty tend to have low median household income (negatively correlated) and the areas that have a high percentage of the non-English speaking population may also have a high percentage of the foreign-born population (positively correlated). The high correlations between two or more independent variables will cause the multicollinearity problem in a regression model. To detect multicollinearity, variance inflation factors (VIF) of the selected independent variables were calculated and the variables with VIF valuable greater than 2.5 were removed from the model one by one (Johnston et al., 2018). The VIF-based multicollinearity analysis results were presented in Table 5 and it was found that only 4 variables can be included in the model.

Table 5 Selected Independent Variables Based on Multicollinearity Analysis

Variable	VIF
CI	1.001494
Percentage of Bachelor’s degree or higher	1.193229
Percentage of Hispanic	1.327218
Percentage of Black	1.203261

After that, according to the P-values of the independent variables from the regression modeling results, the final set of independent variables that have significant impacts on the dependent variable can be identified and the results of the developed final random-effects panel data model are presented in Table 6. It can be seen that there are only two independent variables that are significantly associated with the reduction of transit ridership during the COVID-19 pandemic. They are the COVID-19 Composite Index (CI) and Percentage of Bachelor’s degree or higher. The Goodness-of-fit indexes R-squared is 0.69197, indicating the random effects regression fitted the data well.

Table 6 Results of the Random Effects Panel Model

Variable	Coeff.*	Std. Error	Z value	P-value
CI	0.01021119	0.00045213	22.5848	< 2.2e-16
Percentage of Bachelor’s degree or higher	1.05677359	0.22206443	4.7589	1.95E-06
Intercept	-0.33264141	0.09184855	-3.6216	0.0002928
R-Squared	0.69197			
Adj. R-Squared	0.68937			
Chi-squared	532.411 (df=2); p-value: < 2.22e-16			
Sample size	240			

From the modeling results presented in Table 6, it was found that the ridership reduction rate increased as the COVID-19 CI increased, and the areas with a high percentage of the population with a bachelor’s degree or higher tend to have more transit ridership reductions during the COVID-19 pandemic. More specifically, with all other variables keeping constant, 1 unit increase in COVID-19 CI is associated with 1% more reduction in transit ridership. Similarly, 1% increase of the population with a B.S. degree or higher is associated with about 1.06% more reduction in public transit ridership during the COVID-19 pandemic.

These findings are reasonable and consistent with the findings in the literature. First, the COVID-19 CI measures the level of fear toward COVID-19 in an area. As the level of such fear increases, the public will avoid using public transit to reduce their exposure to the COVID-19 risk, thereby reduction of public transit ridership will increase. Second, as we mentioned in the literature review section, previous studies (Hu and Chen, 2020 and Brough et al., 2020) also found that the transit ridership declined more among the higher educated individuals. The major reason is that individuals with higher education are less likely to engage in jobs that involve a high physical presence and therefore more likely to be able to work remotely (Dingel and Neiman, 2020). On the other hand, the less educated individuals are more likely to work in grocery stores, sanitation, and cleaning, and logistics and are often labeled “essential” workers who are still required to travel to their place of work during the pandemic. Therefore, the difference in the percentage of the population with a B.S. degree or higher becomes a key contributor to the socioeconomic disparities in travel behavior during the pandemic.

4.2 Correlation Analysis

Although the regression model can account for the collective effects of multiple variables, only a few independent variables can be included in the model and identified as variables having significant impacts on the dependent variable. To further investigate the impacts of different independent variables, the traditional correlation analysis method was also used to further identify the factors that are significantly correlated with the dependent variable. For this purpose, the Pearson correlation coefficients between the independent variables and the dependent variable (i.e. YoY ridership reduction rate) were calculated and the results are presented in Table 7, where the independent variables that have significant correlations with the ridership reduction were listed.

Table 7 Correlation Analysis

Variables	Correlation with Dependent Variable	P-value
Median Household Income	0.277235844	1.3112E-05
Percent In Poverty	-0.210951458	0.00100879
Percentage of Bachelor’s degree or higher	0.287724398	5.89E-06
Percentage of Employment Rate	0.190918186	0.00298175
Percentage of Hispanics	-0.157367352	0.01467014
Percentage of Asian	0.171722571	0.00767003

From Table 7, it can be seen that six variables are significantly correlated with the public transit ridership reduction during COVID-19. Following are some key findings:

- The median household income, percentage of bachelor’s degree or higher, percentage of employment rate, and percentage of Asians have positive correlations with the public transit ridership reduction. It means that the areas with higher median household income, a higher percentage of the population with a Bachelor’s degree or higher, a higher employment rate, and a higher percentage of the Asian population have more reductions in public transit ridership.
- The percentage in poverty and percentage of Hispanics have negative correlations with the public transit ridership reduction. It means that the areas with a higher percentage of the population in poverty, and a higher percentage of the Hispanic population tend to have less reduction in public transit ridership.

Among these findings, the findings regarding household income are consistent with the findings in the literature. Brough et al.(2020), Wilbur et al. (2020), and Hu and Chen (2020) all found that the transit ridership in high-income areas has dropped more than in low-income areas during the COVID-19 pandemic.

Chapter 5. Conclusion

In this study, a national-wide study is conducted to investigate the impacts of COVID-19 on the public transit ridership in the top twenty metropolitan areas in the US. At first, the reasons for the ridership decline during the COVID-19 pandemic were discussed based on the findings from the literature. After that, a COVID-19 composite index was developed to qualitatively measure the level of public fear toward COVID-19 in different metropolitan areas. Next, a random-effects panel data model was developed to analyze the impacts of COVID-19 and some socioeconomic factors on transit ridership reduction during the COVID-19 pandemic. In addition, correlation analysis was conducted to further analyze the impacts of the identified socioeconomic factors.

Key findings

According to the results of this study, the following key findings can be obtained:

- The transit ridership for all areas has been reduced significantly, but the reduction rate varies by time and area.
- The level of public fear toward COVID-19 of a metropolitan area has significant impacts on its public transit ridership reduction. Specifically, 1 unit increase in COVID-19 CI is associated with 1% increase in the reduction of transit ridership.
- For different socioeconomic groups, the changes in transit ridership during the COVID-19 pandemic are different:
    - Areas with a high percentage of the population with a bachelor’s degree or higher tend to have more transit ridership reductions. Specifically, 1% increase of the population with a B.S. degree or higher is associated with about 1.06% increase in the reduction of public transit ridership.
    - Areas with higher median household income, higher employment rate, and a higher percentage of the Asian population are more likely to have more reductions in public transit ridership.
    - Areas with a higher percentage of the population in poverty, and a higher percentage of the Hispanic population are more likely to experience smaller reductions in public transit ridership.

Policy implications

The findings of this study can help public transit agencies and local transportation planning organizations better understand the causes and patterns of changes in public transit ridership during the pandemic. Note that, the developed model can be applied to predict the transit ridership for any area of any size because all the dependent and independent variables (including the COVID-19 composite index) used in the model have relative values instead of absolute values. Based on the predicted ridership change, the transit agencies can adjust their service by adding more services in the area where more population depends on public transit while reducing their service in the areas where a high proportion of the population can choose to work from home or shift to other transportation modes. In addition, the local government can also allocate more public transit funding to the areas where a higher percentage of the population depends on public transit to better accommodate their travel needs during the pandemic. Overall, the results of the study can help the public transit agencies and local transportation planning organizations make the right decisions to fully consider both equity and efficiency issues in the public transit system during the pandemic.

Limitations and future study needs

There are several limitations of this study. First, there are some other unobserved factors like government policies and vaccination rates, that may also contribute to the change of public transit ridership. In the future, more data need to be collected to consider the impacts of the vaccination rate and other factors on the recovery of public transit ridership. Second, the data in this study was collected at an aggregated metropolitan-area level which makes it hard to differentiate the significance of the socioeconomic factors. In the future, more disaggregated data need to be collected to further investigate the impacts of socioeconomic factors. Furthermore, this study only analyzed the top 20 metropolitan areas in the US. In the future, data from more metropolitan areas need to be collected to improve the results of this study.

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