Impact of COVID-19 on Public Transit Accessibility and Ridership

Michael Wilbur (corresponding author)
Department of Electrical Engineering and Computer Science
Vanderbilt University
michael.p.wilbur@vanderbilt.edu

Afiya Ayman
Department of Computer Science
University of Houston

Amutheezan Sivagnanam
Department of Computer Science
University of Houston

Anna Ouyang
Department of Electrical Engineering and Computer Science
Vanderbilt University

Vincent Poon
Department of Computer Science
University of Houston

Riyan Kabir
Department of Electrical Engineering and Computer Science
Vanderbilt University

Abhiram Vadali
Department of Electrical Engineering and Computer Science
Vanderbilt University

Philip Pugliese
Chattanooga Area Regional Transportation Authority

Daniel Freudberg
Nashville Metropolitan Transit Authority

Aron Laszka
Department of Computer Science
University of Houston

Abhishek Dubey
Department of Electrical Engineering and Computer Science
Vanderbilt University

ABSTRACT

The novel coronavirus COVID-19 has radically transformed travel behavior in urban areas throughout the world. Foremost, agencies must determine how to provide adequate service while navigating a rapidly changing environment with reduced revenues. Even as COVID-19 related restrictions are lifted, transit agencies are increasingly concerned with their ability to adapt to fundamental changes in ridership behavior and public transit usage. To aid transit agencies in becoming more adaptive to sudden or persistent shifts in ridership patterns, we aim to address three questions. First, to what degree has the COVID-19 pandemic affected ridership of fixed-line public transit and what is the relationship between reduced demand and reduced vehicle trips? Second, how has COVID-19 changed ridership patterns and are these changes expected to persist after restrictions are lifted? Lastly, are there disparities in ridership changes across socio-economic groups and the mobility impaired? We focus on Nashville and Chattanooga, TN where we compare ridership demand and reduced vehicle trips imposed by the two cities. These patterns are compared to anonymized mobile location data to study the relationship between mobility patterns and transit usage. Additionally, we provide a correlation analysis and explanatory multiple variable linear model to investigate the relationship between socio-economic indicators and changes in transit ridership. Lastly, we include an analysis of changes in paratransit demand before and during COVID-19. We find that ridership initially dropped by 66% and 65% over the first month of the pandemic for Nashville and Chattanooga respectively before starting a moderate recovery. Additionally, cellular mobility patterns in Chattanooga indicate that foot traffic recovered to a greater degree between mid-April, 2020 and the last week in June, 2020 than transit ridership. Our models show that education level had a statistically significant impact on change in fixed-line bus transit. Lastly, we found that the distribution of changes in demand for paratransit services are similar to to our findings from fixed-line bus transit.

Keywords: COVID-19, ridership, socioeconomics, spatiotemporal, paratransit

INTRODUCTION

The novel coronavirus COVID-19 has radically transformed travel behavior in urban areas throughout the world. While COVID-19 has affected normal operations in almost all industries, the social distancing measures and precautions associated with this virus have had particularly devastating effects on public transit. For instance, since the World Health Organization (WHO) declared COVID-19 a pandemic on March 11, 2020 [1] subway ridership in New York City dropped by upwards of 91% [2]. Given that public transit already operated at a loss prior to COVID-19 [3], this disruption has created pressing operational challenges for public transit agencies.

Foremost, agencies must determine how to continue providing adequate service while navigating a rapidly changing environment with reduced revenues. Even as COVID-19 related restrictions are lifted, transit agencies are increasingly concerned that the systemic shock of COVID-19 has caused fundamental changes in ridership behavior and public transit usage. Therefore, it is not guaranteed that revenues will return to pre-COVID levels. Additionally, COVID-19 accelerated remote and hybrid work options. In this way, transit agencies are unsure as to whether traditional assumptions regarding transit behavior still hold.

Faced with drastic drops in revenues, transit agencies rapidly reduced vehicle trips to keep costs under control. However, a reduction in transit accessibility disproportionately impacts populations who are already disadvantaged, including lower-income populations who cannot afford personal vehicles [4] or people with disabilities. As lower-income populations are more likely to rely on the public transit system to get to work, school or access child services, agencies must take care in identifying transit vehicle trips to cut so as to not hurt those most reliant on local transit services.

Additionally, mobility impaired transit users are often over-looked and should be taken into account in future planning. According to the US Census Bureau, in 2014 nearly one-in-three adults 18 and older have a disability, one-in-five have a severe disability and one-in-ten have a disability that requires assistance [5]. This group is often reliant on paratransit services, which are services provided by transit agencies as a supplement to fixed-route services to ensure equity for disabled people. Providing adequate access to paratransit is of critical societal importance, and while it is expensive, the societal benefits of a robust paratransit system far exceed its costs [6]. As current research continues to provide insights regarding the impact of COVID-19 on various transit modes, there has been a negligible focus on changes in demand for paratransit services.

We are primarily concerned with the following questions. First, to what degree has the COVID-19 pandemic affected ridership of fixed-line public transit and what is the relationship between reduced demand and reduced vehicle trips? We focus on Nashville and Chattanooga, TN. Second, how has COVID-19 changed ridership patterns and are these changes expected to persist after restrictions are lifted? While this is impossible to know for certain, we provide a spatio-temporal analysis of bus ridership decline to generalize broad changes in ridership patterns. We also compare ridership declines to anonymized mobile location data to look at whether public transit users have switched to personal vehicles. Third, are there disparities in ridership changes across socio-economic groups and the mobility impaired? For this we provide a correlation analysis and explanatory linear model to investigate the relationship between socio-economic indicators and drop in transit ridership. We also include an analysis of changes in paratransit demand before and during COVID-19.

Ultimately, the investigative analysis provided in this work aims to be a starting point for transit agencies to become more adaptive to sudden or persistent shifts in ridership behavior.

Therefore, we highlight the importance of modeling the socio-economics of ridership behavior so that transit agencies can reduce or expand vehicle trips such that those most reliant on public transit and paratransit services have adequate access. In this way, transit agencies can be better informed about their own operations and can plan for future events accordingly.

CONTRIBUTIONS AND KEY FINDINGS

The primary contributions of this work are as follows:

1. We outline the operational changes Nashville and Chattanooga imposed following the start of the COVID-19 pandemic. We find that ridership declines were largely uncorrelated with changes in the number of vehicle runs in both cities.
2. We provide a summary of ridership changes due to COVID-19 in both cities. We find that ridership initially dropped by 66% and 65% over the first month of the pandemic for Nashville and Chattanooga respectively before starting a moderate recovery and stabilizing three months later.
3. A temporal investigation of ridership before and during COVID-19 shows an out-sized proportion of changes in ridership occur on weekdays during the morning and evening rush hours, indicating a potential persistent shift towards alternative work options or possibly a shift to personal vehicles for commuters. Cellular mobility patterns in Chattanooga indicate that foot traffic recovered to a greater degree than transit ridership between mid-April, 2020 and the last week in June, 2020.
4. Our spatial analysis indicates that changes in ridership varies greatly across census tracts and neighborhoods. We found that ridership declined up to 19% more in high-income neighborhoods than in the lowest income parts of Nashville. Additionally, our models show that education level had a statistically significant impact on change in ridership at the aggregate level (per census tract).
5. We performed a temporal investigation of ridership before and during COVID-19 for paratransit services in Nashville and find that the distribution of changes in demand are similar to our findings from our analysis of fixed-line bus transit.

The remainder of this article is as follows. First, we summarize recent literature regarding the impact of COVID-19 on public transit systems and socio-economic transportation studies. Then we describe the data and processing methods, followed by our analysis methods and results. Finally, we summarize our key findings, present implications of this work for transit agencies and discuss possible limitations of this study.

RELATED WORK

In this section we cover literature related to COVID-19 in the context of transportation systems and the interaction of socio-economics and transit usage.

COVID-19 and transportation

Fixed-line bus and rail public transit inherently involves moving passengers in an enclosed space. One of the major reasons there has been significant declines in public transit ridership is the fear of COVID-19. In public health fields, the study of infectious disease transmission through public transit and air travel is well studied [7], [8], [9], [10]. While there is a growing number of publications regarding the spread of COVID-19 by air travel [11], there is a lack of information on how this applies to public transit [12]. Regardless of transmission rates on public transit, ridership on fixed-line bus transit has declined significantly as we show in this work.

Recent work on the impact of COVID-19 on urban transportation shows that decrease in public transport ridership ranged from 40% to 80% for bus systems throughout Europe and the United States [13], [14], [15]. A study in New York showed that average subway and commuter rail ridership is down 80% while bus ridership is down 50% in the first week of July, 2020 with a peak subway ridership decline of 94% in late March [2, 16]. There has been work showing that the types of tickets sold has changed as well. In Sweden, riders mostly switched from monthly period tickets to single tickets and travel funds. Also, tickets typically used by tourists dropped to almost zero, showing that the way in which riders are interacting with fixed-line transit has changed [13].

There has been some recent work investigating mode shift away from public transit. While modeling lasting effects of the pandemic is in its early stages, in some high transit cities even moderate shifts from public transit to personal vehicles can increase travel times by 5 to 10 minutes on average for one way trips [17]. On the other hand, in New York City the bike sharing program CitiBike has been more resilient to loss in ridership than the subway system and there is some evidence of transit users shifting to shared bike programs [18].

Socio-economics and equity in transportation

Previous research indicates different transit behaviors among socio-economic classes. When it comes to public transit, low-income and historically marginalized groups are particularly reliant on public transportation [19]. In this context, low-income groups are more likely to ride buses while high income individuals are more likely to utilize rail systems [20]. According to a 2017 publication from the American Public Transportation Association, 30% of bus riders have a household income of less than $15,000, while 12% of bus riders have a household income of $100,000 or more. Among rail riders only 13% have household incomes below $15,000, while 29% have household incomes of $100,000 or more [21].

In terms of public transit versus privately owned mobility options, a study conducted in Hawaii reported key differences between bus riders and solo drivers. The mean household income of a bus rider was 16% lower than that of a solo driver [22]. Bus riders also, on average, owned fewer cars per household (1.7 cars) compared to solo drivers (2.3 cars) [22]. A major reason low-income groups are heavily reliant on public transportation is their lower likelihood of owning a personal vehicle. According to an analysis of 2012 California Household Travel Survey data, 78% of households without a car do not have a car as a result of economic or physical barriers [4]. Together, these studies suggest that individuals of a lower socio-economic background may be disproportionately impacted by changes in public transit availability. It is important to note that these trends are not unique to the United States; a case study conducted in France found that low income individuals comprised a larger portion of public transit ridership than high income individuals [23].

However, the magnitude of these discrepancies between mode choice and socio-economic background is not uniform when comparing transit systems in different urban centers [19]. In a study of mode choice by income level in Atlanta, Los Angeles and New York, Schweitzer shows that bus riders in Atlanta and Los Angeles are disproportionately low income, however these findings are not mirrored for New York [19]. Additionally, while bus riders are disproportionately African American and Hispanic in Atlanta and Los Angeles, the demographics of mode choice in New York mirror those of the urban population generally [19]. This shows that the relationship between income level, demographics and mode choice is dependent on the mode choices available and the equity of the underlying transit system. Therefore it is important for transit agencies to monitor ridership dynamics and changes over time to adequately make informed decisions regarding equity. This becomes critically important when faced with drastic, sudden shifts in ridership behavior in the case of COVID-19 restrictions.

Paratransit is a critical mode of travel for mobility impaired users. Paratransit is demand-responsive in that trips are requested from users ahead of time and aims to bridge gaps in accessibility in public transit. One example of a gap in accessibility is subway or bus stops that are not wheelchair accessible. In New York for instance, 55% of the population uses public transit to travel to work however only 20% of subway stations are wheelchair accessible [24]. Research indicates that the total benefits of paratransit to society far exceed its costs [6].

Research gaps

While socio-economics and equity is well studied in relation to public transit operations, there has been limited work on how COVID-19 has impacted these dynamics. We aim to address this both from the view-point of demand and supply. In terms of demand we look to understand the relationship between socio-economics and public transit ridership. In terms of supply, we look at reductions in vehicle trips. Additionally, despite its importance, to our knowledge the impact of COVID-19 and sudden shifts in user demand have not been studied in the context of paratransit services.

DATA COLLECTION AND PROCESSING

In this section we outline the datasets used in this work which consist of transit and paratransit ridership boarding information, economic data per census tract and COVID-19 cases per day. We also cover our data processing and filtering methods.

Ridership and paratransit data

Boarding count data was provided by the Nashville Metropolitan Transit Authority (MTA) for the fixed-line bus system of Nashville from January 1, 2019 to July 1, 2020. Boarding data was also acquired from the Chattanooga Area Regional Transportation Agency (CARTA) between January 1, 2020 to July 1, 2020. The ridership data was derived from farebox units on all passenger vehicles servicing trips within these time ranges. The farebox data included a record of each passenger boarding event. It also included driver information, a unique vehicle identifier, shift changes and when vehicles switch routes. The farebox data did not, however, include alighting information. The farebox data was filtered so that only boarding events remained. In 2020 there were 2.8 million documented boardings in Nashville between January 1, 2020 and July 1, 2020 and for Chattanooga there were 465k documented boardings between January 1, 2020 and July 1, 2020. Each row in the respective datasets corresponded to a single boarding event.

As complete data was available for Nashville, TN in 2019 we derived baseline ridership metrics by comparing weekly data in 2020 directly to the corresponding week in 2019. Additionally, the full 2019 data provided GPS locations which allowed for spatial comparisons to baseline ridership. For Chattanooga we were provided with aggregated monthly total boardings in 2019.

TABLE 1 : Boarding counts before and after processing and number of census tracts for Nashville and Chattanooga datasets.

	Raw Boardings (2020 YTD)	Processed Boardings (2020 YTD)	Number of Census Tracts
Nashville	2,800,000	2,800,000	120
Chattanooga	464,570	445,987	82

For baseline calculations related to Chattanooga we compared each week in 2020 with the mean ridership per week in the corresponding month from 2019. For Nashville, the GPS location of the vehicle at the time of boarding was available for each boarding event. However for Chattanooga, missing GPS readings were significant. Therefore to add GPS locations to the ridership data in Chattanooga we joined the ridership data with a separate telemetry dataset from on-board devices provided by ViriCiti [25], which included GPS readings and unique identifiers. For each boarding event we used the unique vehicle identifier in the farebox data to find the nearest GPS reading in the ViriCiti dataset. We filtered out boarding events that did not have a GPS reading within a 60 second window of the boarding event. After this process we found that approximately 4% of ridership boardings were removed from the Chattanooga ridership dataset. Once the ridership datasets were prepared, we used the GPS location of each boarding event to assign that event to a 2010 Census Tract. An overview of the total number of boardings, boardings after processing and the number of census tracts in both cities is provided in Table 1.

Paratransit data was provided by Nashville MTA for a two week period from on April 28, 2020 to May 11, 2020 as well as from April 26, 2019 to May 9, 2019. There were a total of 16,490 passenger trips in the 2019 dataset and a total of 5,578 passenger trips in the 2020 dataset.

Economic data, cellular mobility data and COVID-19 new case counts

Economic data was retrieved from the United States Census Bureau [26] and ProximityOne [27]. These sources provided a breakdown of racial demographics, income levels and housing information of residents in each 2010 census tract. Additionally, we accessed Longitudinal Employer-Household Dynamics data from the United States Census Bureau [28] to extract workplace demographic data from the Origin-Destination Employment Statistics (LODES) dataset. The LODES data provided socio-economic information on workers employed in a census tract. This included the number of workers in a census tract that were White, African American, Hispanic as well as the number of workers with or without a college degree and the number of jobs in various fields such as education, entertainment and food services. In this case, if a person with with a college degree lives in census tract i but works in census tract j, the socio-economic indicators of this job would be attributed to census tract j in the LODES dataset. In this work, we refer to socio-economic indicators in census tract i as “residence” indicators and socio-economic indicators in census tract j as “workplace” indicators.

Anonymized mobile location data was acquired from SafeGraph [29] for Hamilton County (including Chattanooga, TN) from January 1, 2020 through July 1, 2020. The mobility data included 4,812 places of interest (POIs) throughout the region, 4,800 of which were in CARTA’s operational boundary. Each POI included the number of unique visitors per day and the latitude, longitude location of the POI. This dataset was used to represent mobility patterns within the Chattanooga region. Additionally, new COVID-19 cases per day for Nashville and Chattanooga

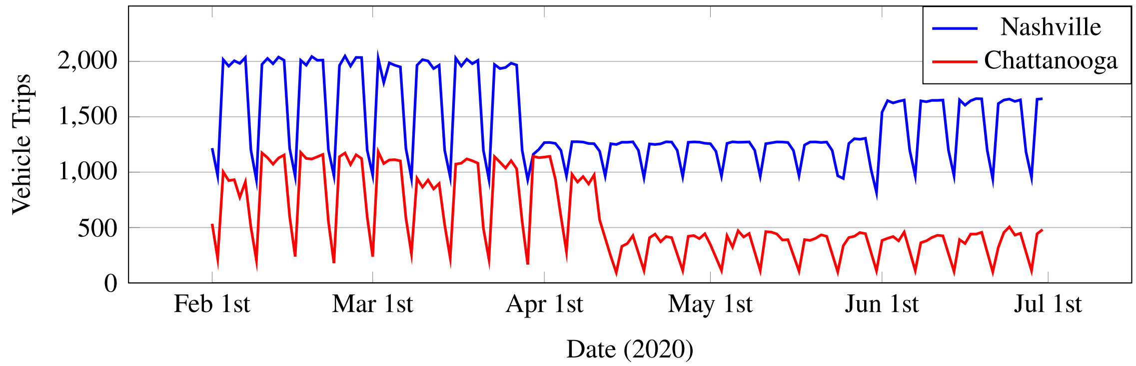


FIGURE 1 : Daily number of vehicle trips for Nashville and Chattanooga from February 1, 2020 to July 1, 2020.

were retrieved from The New York Times COVID-19 Dashboard [30] between January 1, 2020 and July 1, 2020.

Mapping boarding events to census tracts

To incorporate the census tract level economic data, each boarding event was mapped to the corresponding census tract where that boarding occurred. As each census tract included a geometric polygon representing the tract this was a simple spatial join. One limitation of working with aggregated 2019 data for Chattanooga was that we could not get baseline ridership information at the census tract level. For Nashville baseline 2019 ridership at the census level was available.

ANALYSIS AND RESULTS

In this section we outline the main analysis and results for this work. We start by giving a high level overview of COVID-19 restrictions and the corresponding operational changes implemented by the transit agencies in Nashville and Chattanooga before moving into our analysis of ridership declines in both cities. We then present the socio-economic analysis and associated models. Finally, we present findings related to paratransit operations.

COVID-19 restrictions and operational changes

Nashville and Chattanooga both receive guidance regarding COVID-19 related restrictions directly from the State of Tennessee. Both cities are able to impose their own regulations in excess of the state's recommendations. On March 5, 2020 the first COVID-19 case was identified in Tennessee and on March 8, 2020 the first COVID-19 case was found in Nashville. The State of Tennessee ordered a State of Emergency regarding the pandemic on March 12, 2020 and a Safer at Home order on March 30, 2020 which mandated residents of the state stay in their homes other than for "essential activities". The Tennessee Safer at Home order ended on April 30, 2020 [31].

Nashville regulations were more swift. Nashville imposed their own Stay at Home order on March 22, 2020 which was not lifted until Phase 1 reopening began on May 11, 2020. The Phase 1 reopening in Nashville allowed gatherings of up to 10 people while most businesses were allowed to open at 50% capacity. On May 25, 2020 Nashville moved to Phase 2 which allowed gatherings of up to 25 people and most businesses could operate at 75% capacity [32]. Nashville moved to a Phase 3 opening on June 20, 2020 which included provisions for a limited opening of small venues (up to 250 people) however reverted back to a Phase 2 opening on July 3, 2020.

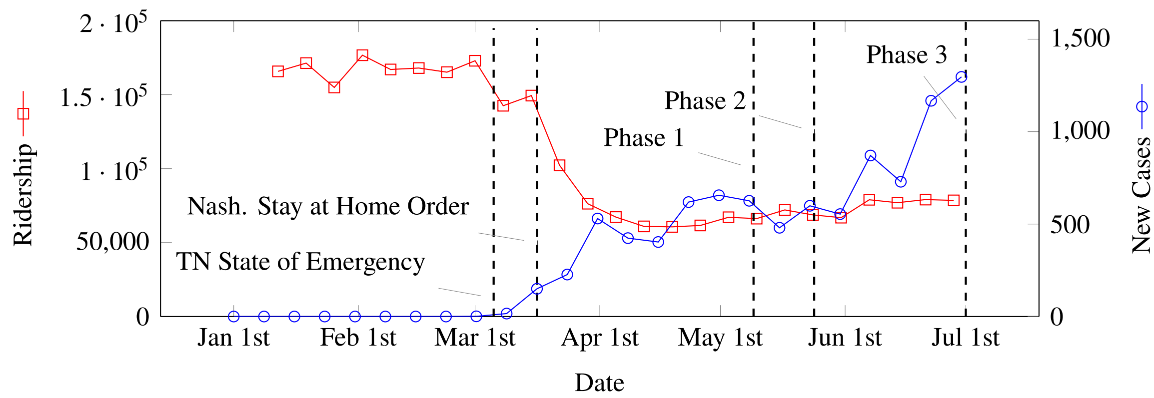
Both Nashville and Chattanooga reduced the total number of vehicle runs in reaction to the initial reduced demand at the start of COVID-19. Unique trip identifiers were not available in either dataset. Therefore to tally the number vehicle trips serviced per week we grouped the data by date, unique driver ID, unique vehicle ID, route and direction. The number of daily vehicle trips for Nashville and Chattanooga is shown in Figure 1. Chattanooga moved to a reduced bus schedule in the middle of April while Nashville switched to a reduced schedule on March 29, 2020. Prior to the schedule change, Chattanooga serviced an average of 6,100 vehicle trips per week. During the week of April 19, 2020 Chattanooga switched all weekdays to their Saturday schedule which reduced the average weekly number of vehicle trips to 2,600, a decline of approximately 57%. Nashville switched to a reduced schedule during the week of April 1, 2020. Prior to switching, Nashville serviced an average of 12,206 weekly vehicle trips which was reduced to an average of 8,324 weekly vehicle trips from the week of April 5, 2020 to the week of May 24, 2020 which was a 31% reduction in vehicle trips. Starting in June, Nashville increased the number of vehicle trips to an average of 10,358 trips per week, a 17% reduction from pre-COVID operations.

Impact of COVID-19 on city-wide ridership

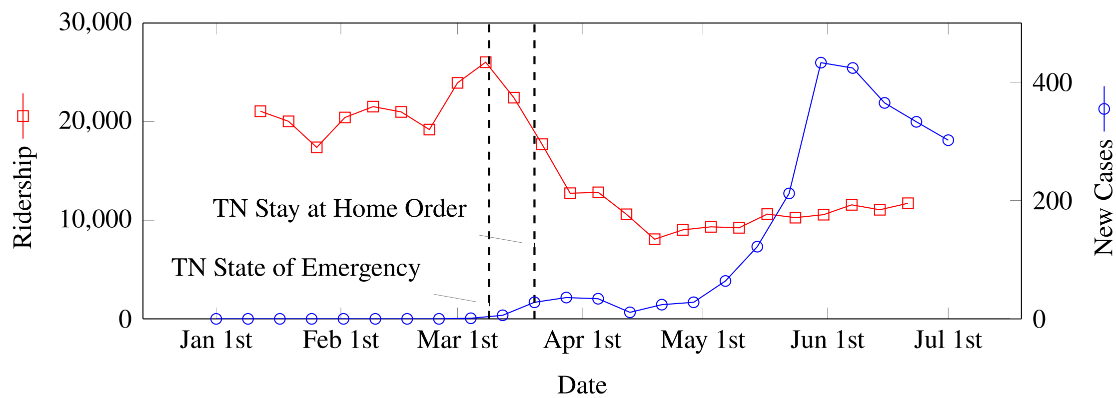
The fundamental question in this section is to what degree has COVID-19 decreased ridership from a global, system-level perspective. Additionally, to what degree can these changes be attributed to changes in demand versus changes in supply. Figure 2a and Figure 2b show weekly total ridership and weekly new COVID-19 cases in Nashville and Chattanooga respectively. Figure 2c shows drop in ridership for Nashville and Chattanooga compared to their 2019 baseline.

As shown in Figure 2a, Nashville public transit ridership started to decline on the week of March 1, 2020 which corresponded with the first known COVID-19 case in Tennessee on March 5, 2020 and the Tennessee State of Emergency Order on March 12, 2020. Perhaps more importantly there was a major tornado in Nashville on March 3, 2020 [33] which helps explain the initial decline in ridership at this time. Ridership remained constant for a week before a significant decline started during the week of March 22, 2020 when the Nashville Safer at Home Order started. Nashville ultimately reached a low of 60,620 riders on the week of April 19, 2020 which was a 66% reduction in ridership compared to the 2019 baseline as shown in Figure 2c. Ridership then stabilized and by the week of June 28, 2020 ridership in Nashville had recovered 22% from the low in April, 2020. Chattanooga's steep decline started the week of March 5, 2020 before hitting a low also on the week of April 19, 2020 of 8,077 weekly riders, representing a 65% loss in ridership compared to the 2019 baseline. Ultimately Chattanooga ridership recovered to 11,725 riders the week of June 28, 2020 which was an increase of 45% from the low in April, 2020.

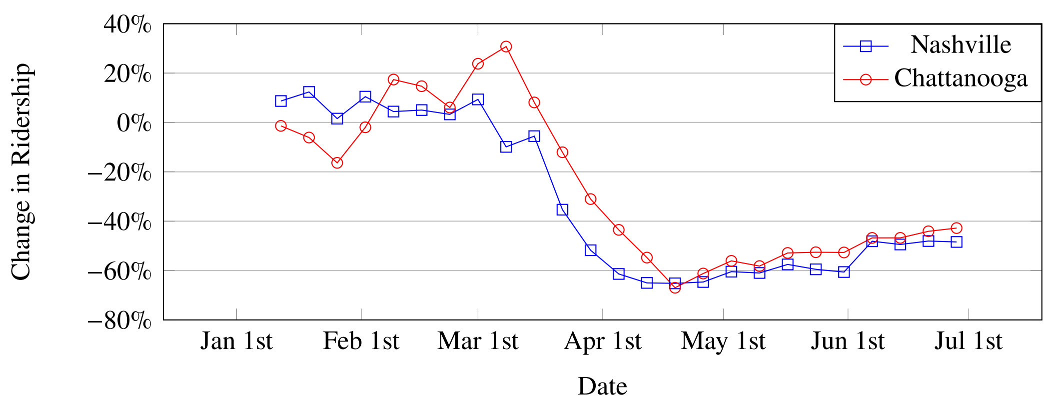
Ultimately, both cities saw a rapid decline in fixed-line bus ridership from early March to late April, 2020 before ridership stabilized through the end of June, 2020. In both cases, the initial rapid decline in ridership occurred well before vehicle trips were reduced in either city. The magnitude of ridership decline was similar at each stage in both cities, despite the fact that Nashville and Chattanooga had cut vehicle trips by differing amounts. Between early March and late April, 2020, both cities saw similar rapid declines in ridership despite the fact that Chattanooga reduced the total number of vehicle runs by 57% following the start of COVID-19 and Nashville initially reduced the total number of vehicle runs by only 31%. Even though Nashville added capacity in early June, 2020 both cities stabilized at similar ridership declines through the remainder of the month. Therefore, in these two cities ridership decline was likely driven mostly by low ridership



(a) Nashville

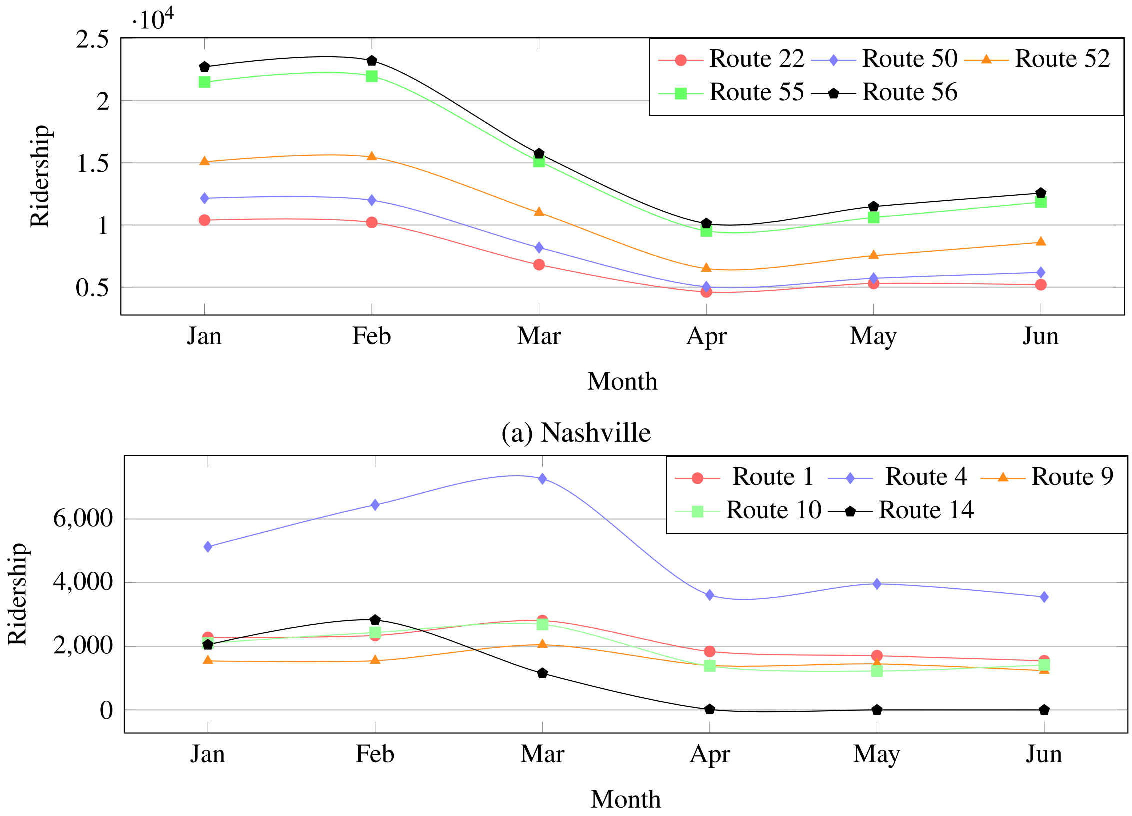


(b) Chattanooga



(c) Change in ridership for Nashville and Chattanooga

FIGURE 2 : Weekly ridership and new COVID-19 cases per week for (a) Nashville and (b) Chattanooga. (c): Change in ridership compared to 2019 baselines for Chattanooga and Nashville, TN from January through June 2020.



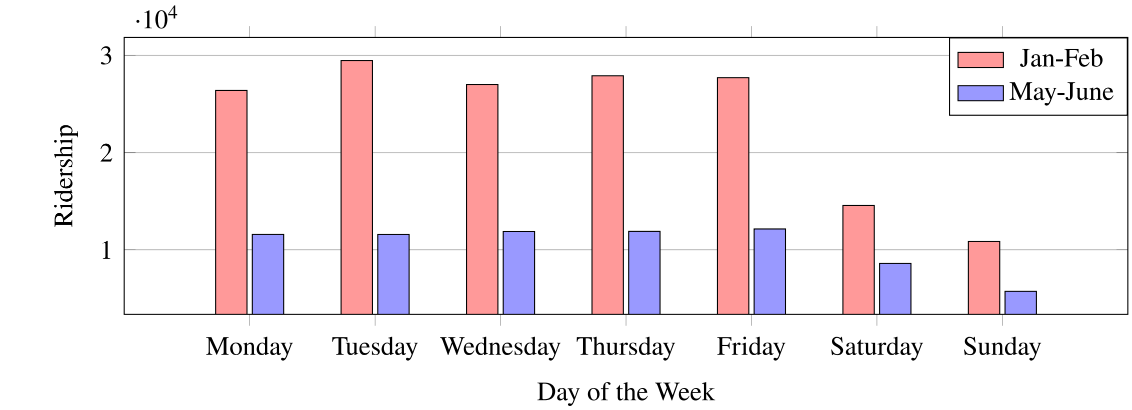
(b) Chattanooga

FIGURE 3 : Ridership by month for the 5 most popular routes in (a) Nashville and (b) Chattanooga in 2020.

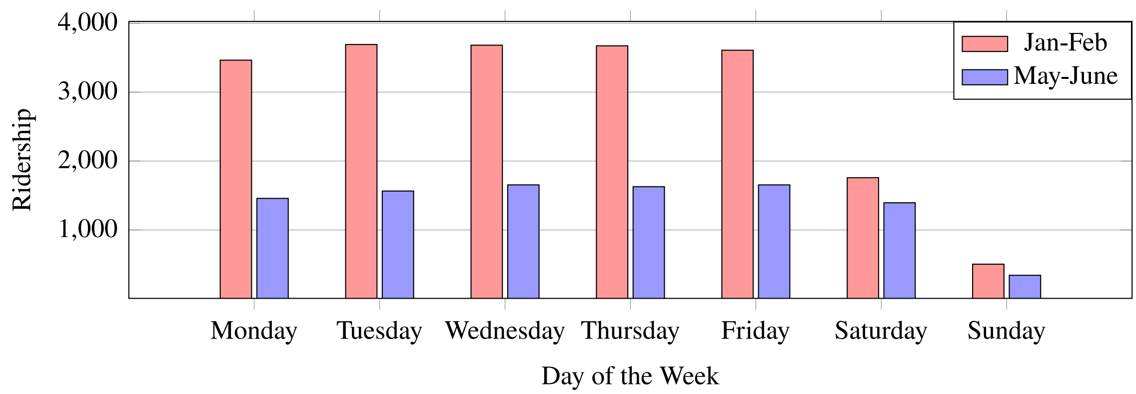
demand.

Route level investigation

Figure 3a and Figure 3b show the monthly ridership distribution on the top 5 routes for the cities of Nashville and Chattanooga respectively. We see similar trends to the aggregated ridership analysis in the previous section. In both cities, ridership decreased rapidly before stabilizing in April, 2020. In Nashville however, we see a greater rebound between April to June, 2020 than in Chattanooga. The rebound in Nashville corresponds loosely with Phase 2 reopening. An important note is that route 14 in Chattanooga is one of the most used routes, however it is unique in that it is a free shuttle service to the University of Tennessee, Chattanooga. When Universities went online in March, 2020, route 14 initially continued operating on its regular Saturday schedule. Due to the drastic demand reduction during this time Chattanooga ultimately stopped the service entirely on April 5, 2020. Ultimately, we see that the most populated routes follow a similar trajectory and magnitude of ridership drop as the fixed-line transit system overall. Therefore a more detailed spatio-temporal analysis is outlined in the following sections of this paper.



(a) Nashville



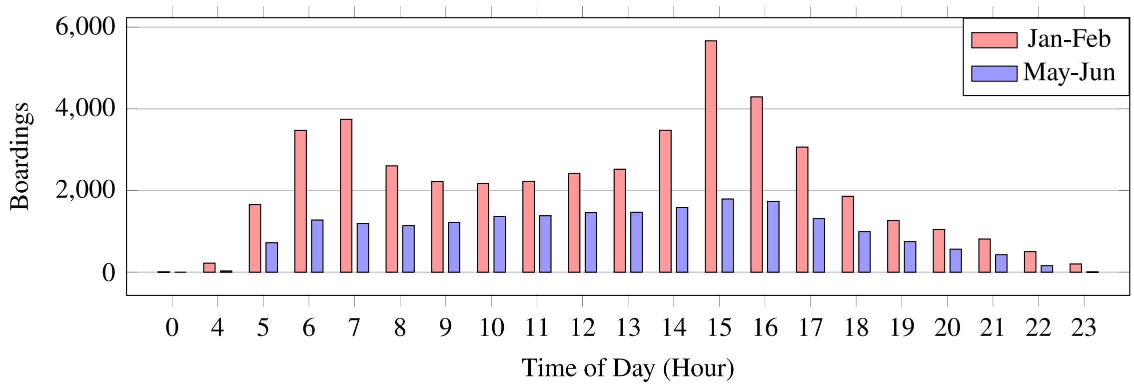
(b) Chattanooga

FIGURE 4 : Average ridership by day for January–February and May–June 2020 for (a) Nashville and (b) Chattanooga. January–February represents baseline pre-COVID ridership levels in 2020 while May–June represents ridership after it stabilized mid-COVID.

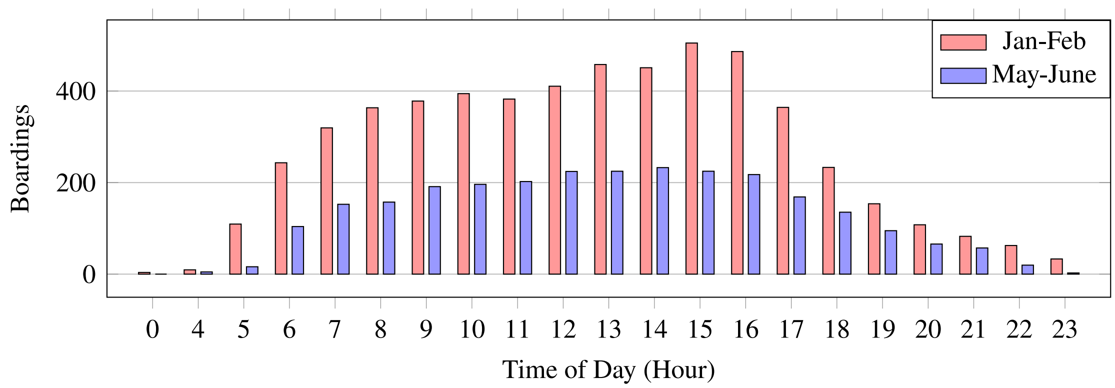
Spatio-temporal analysis of transit usage and rider behavior

Here we investigate spatio-temporal changes in ridership between pre-COVID and mid-COVID operations. For both cities normal operations spanned from January 1, 2020 to the end of February, 2020 and after a rapid drop in ridership, stabilized in mid-to-late April, 2020. Therefore we use January-February to represent pre-COVID operations and May-June to represent mid-COVID operations. In Figure 4a and Figure 4b, we see the ridership distribution of Nashville and Chattanooga for each day of the week for pre-COVID and mid-COVID operations. In both cities the drop in ridership on the weekends is less than weekdays with Chattanooga only seeing a 20% decrease in ridership on Saturdays and a 32% decrease on Sundays compared to an average of 56% on weekdays. Nashville saw a 41% decrease in ridership on Saturdays and a 47% decrease on Sundays compared to an average of 57% decrease for weekdays.

Figure 5a and Figure 5b show ridership pre-COVID compared to ridership mid-COVID per hour of the day. The biggest drops in ridership occur during morning rush and evening rush. This is highlighted in Nashville where morning rush (5:00AM-9:00AM) saw a 64% change in ridership and evening rush (3:00PM-6:00PM) saw a 62% decrease compared to a 42% change between 9:00AM and 3:00PM. This discrepancy was not as pronounced with Chattanooga where there was



(a) Nashville



(b) Chattanooga

FIGURE 5 : Average weekday boardings by hour of day for January–February and May–June 2020 for (a) Nashville and (b) Chattanooga. January–February represents baseline pre-COVID ridership levels in 2020 while May–June represents ridership after it stabilized mid-COVID.

a 62% and 56% decrease in ridership for morning and evening rush respectively compared to a 53% between 9:00AM and 3:00PM.

Figure 6 shows weekly transit ridership compared to visits to points of interest (POIs) from anonymized mobile location data [29] from January, 2020 to July, 2020 in Chattanooga, TN. As shown, mobility in Chattanooga starts to drop the week of March 15, 2020, the same week transit ridership starts a steep decline. The weekly low for mobility was the week of April 12, 2020 in which there were 127,185 visits to POIs and 10,602 transit rides. The weekly low for transit ridership was one week later during the week of April 19, 2020 in which there were 8,735 transit rides and 151,210 visits to POIs. After their respective lows, mobility and transit ridership both recover through May and June 2020. There were 268,868 visits to POIs and 11,725 transit rides during the week of June 21, 2020 which represented a 111% and 10% increase in mobility and transit ridership respectively between the weeks of April 12, 2020 (weekly low for mobility) and June 21, 2020. Between the weeks of April 19, 2020 (weekly low for transit ridership) and June 21, 2020 there was a 78% and 45% increase in mobility and transit ridership respectively.

Figure 7 shows the percent decrease in ridership between pre-COVID (January-February) and mid-COVID (May-June) operations per census tract. As shown, change in ridership was not uniformly distributed throughout either city. Both cities see significant decreases downtown, most

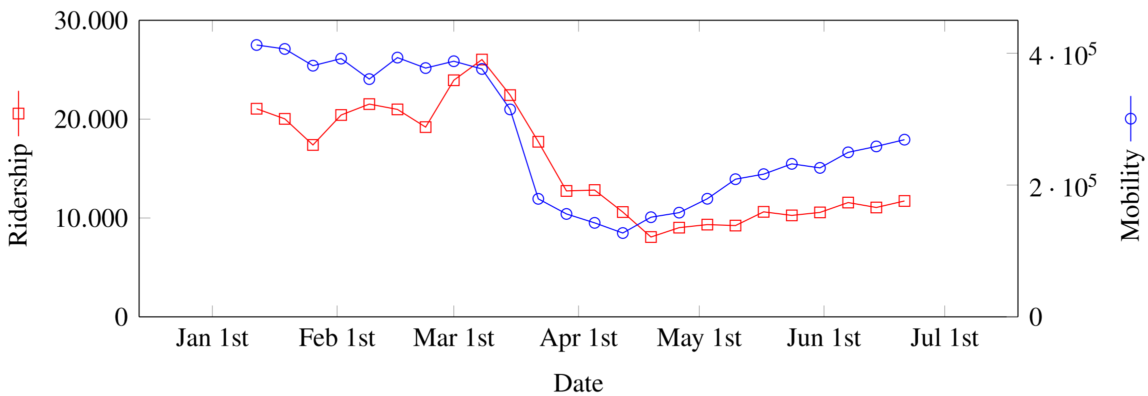
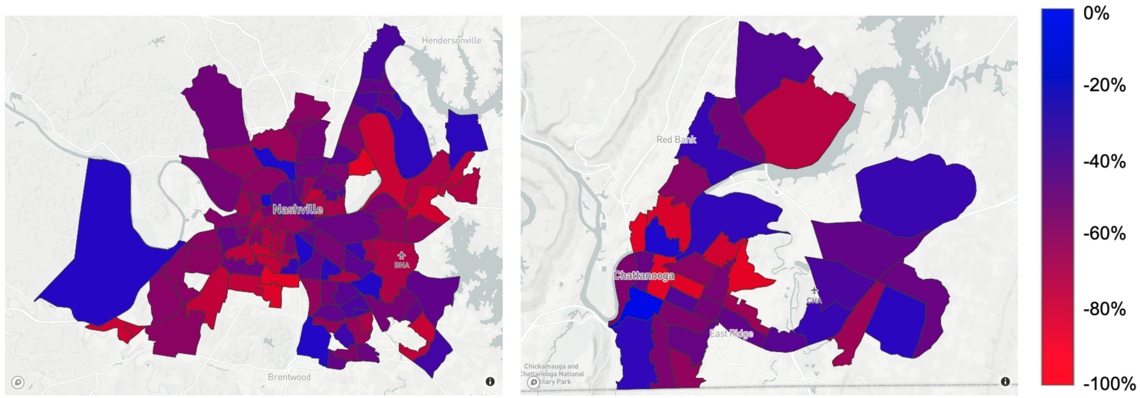


FIGURE 6 : Chattanooga weekly ridership: weekly ridership compared to mobility (anonymized mobile location data) in Hamilton County from January through July 2020.



(a) Nashville (b) Chattanooga .

FIGURE 7 : Change in ridership between pre-COVID (January–February) and mid-COVID (May–June) 2020 per census tract for (left) Nashville and (right) Chattanooga.

likely due to workers working remotely. This was most visible in Chattanooga where ridership decreased by up to 81%. Chattanooga also saw a significant decrease in ridership in the census tract that contains the University of Tennessee, Chattanooga reflecting the University's decision to suspend in-person operations and CARTA's subsequent cancellation of the free shuttle servicing this region. While the same patterns are present in Nashville, change in ridership was more uniform, likely due to the density of Nashville's downtown region. Nashville saw significant decreases in ridership from areas heavily dependent on retail and shopping including a 87% drop to Opry Mills and a 86% drop to Green Hills, which are the two largest shopping malls in Nashville.

As we can see in this section, the biggest declines in ridership were on weekdays during morning and evening commuting times. Additionally, the comparison of transit ridership to mobility patterns in Chattanooga indicates that foot traffic recovered to a greater degree than transit ridership. Therefore, there are likely two competing factors at play. First, the declines in transit ridership on weekdays during morning and evening commuting times indicate a possible persistent shift towards alternative work options throughout the COVID-19 pandemic. On the other hand, the greater recovery in mobility from the cellular dataset indicates a possible shift away from public

TABLE 2 : Overview of key demographics for Nashville and Chattanooga.

	Total Population	Median Family Income	Median Housing Value	Median Gross Rent	White	African American	Hispanic
Nashville	650,806	65,317	206,464	967	63%	27%	10%
Chattanooga	348,856	63,552	165,259	809	75%	20%	5%

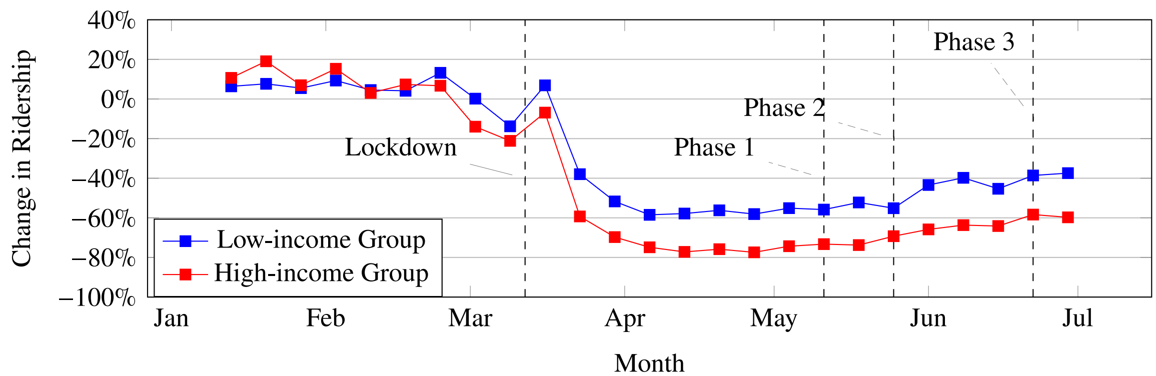


FIGURE 8 : Change in ridership compared to 2019 baseline for the 10% high income and 10% lowest income census tracts in Nashville measured by median household income.

transit options. Lastly, the spatial variation in transit ridership shows that changes in ridership is not uniform throughout Nashville and Chattanooga.

Socio-economic analysis and explanatory model

In this section we investigate the relationship between decreases in ridership and socio-economic factors. An overview of the demographics for both cities is provided in Table 2 to provide perspective as to the make-up of the cities in this study. Our investigation includes three components: Figure 8 shows change in ridership between high-income and low-income tracts, Table 3 shows Pearson correlation values between a set of independent variables and relative ridership change while Table 4 presents a linear regression analysis for identifying statistically significant associations.

Figure 8 shows change in weekly ridership for 2020 compared to baseline ridership in 2019 for the 10% highest income and 10% lowest income census tracts in Nashville. We see a greater decrease in ridership for the high income compared to the low income group (77% vs 58%). The lows for both groups occurred during the week of April 27th. The trend lines follow a similar trajectory for both groups; no significant time shift was found. Additionally, both groups saw similar upward trends in ridership following their respective lows during the week of April 27, 2020.

The economic data from the United States Census Bureau [26] includes a breakdown of racial demographics, income levels and housing information for residents at the census tract level. We refer to this category of socio-economic variables as "residence" variables. Additionally, from the LODES dataset [28] we extracted socio-economic information on workers employed in jobs within a census tract, which are referred to as "workplace" variables. In total there are 120 census tracts in Nashville. Additionally, some census tracts had very few boardings on average. To

TABLE 3 : Pearson correlation values for relative change in ridership after COVID-19 in Nashville Tennessee. Positive correlation indicates that a larger independent variable leads to a larger relative impact, i.e. a greater decrease in ridership. Residence variables refer to demographics of those who live in the target census tract, workplace variables refer to demographics of jobs located in the target census tract. Per Table 4, *% of jobs - no college degree* is the only statistically significant variable. Sample size of 94 census tracts.

Metric	**Category**	**Pearson Correlation**
Median Income	Residence	0.21
Median Housing Value	Residence	0.35
Median Rent	Residence	0.15
% White	Residence	0.01
% African American	Residence	-0.02
% Hispanic	Residence	-0.19
% of jobs - White	Workplace	0.12
% of jobs - African American, Hispanic	Workplace	-0.06
% of jobs - no college degree	Workplace	-0.43
% of jobs - with college degree	Workplace	0.20
% of jobs - entertainment, and food services	Workplace	0.17

avoid outliers due to sparsely serviced census tracts, only tracts that had at least an average of 10 boardings per day between May 1 to July 1 2020 were considered, resulting in a sample size of 94 census tracts. For the analysis in Table 3 and Table 4 we investigate the relationship between the independent variables and change in ridership between May 1 to July 1 2020 compared to the same time period in 2019 per census tract in Nashville. As for coefficients signs, a positive Pearson correlation Table 3, and subsequently a positive coefficient in Table 4, indicates that a larger independent variable leads to a larger relative impact, i.e. a greater decrease in ridership compared to the 2019 baseline.

In Table 3, the highest positive correlation with drop in ridership was *median housing value* (0.35), i.e. census tracts with high median housing costs had a greater reduction in ridership from the 2019 baseline. Regarding workplace demographics, we see a moderate negative correlation of -0.43 between the percentage of jobs held by workers without a college degree and drop in ridership. In this case, the more jobs in a census tract held by workers without a college degree indicated a less severe drop in ridership.

It is important to note that while the correlation values presented in Table 3 can be useful for providing insight to transit decision-makers at a high level, it does not statistically indicate association. To further interpret the relationship between the socio-economic variables and ridership we designed a multiple linear regression model using Ordinary Least Squares (OLS). There are two challenges in crafting a multiple linear regression model in this setting. First is the potential for multicollinearity among the independent variables. In this setting, *median income*, *median housing value* and *median rent* are highly correlated, therefore we removed *median income* and *median rent*, leaving *median housing value* since this variable had the highest Pearson correlation of the three. Additionally, *% of jobs - no college degree* and *% of jobs - with college degree* are highly related.

TABLE 4 : Socio-economic model for relative change in ridership between May 1 to July 1 2020 compared to 2019 baseline per census tract in Nashville. A positive coefficient indicates that a larger independent variable leads to a larger relative impact, i.e. a greater decrease in ridership. Sample size: 94 census tracts, R^2: 0.221, Adjusted R^2: 0.184, F-statistic: 5.901

Variable	Category	Coefficient	Std.Error	Z-value	P-value
CONSTANT	-	0.556	0.015	36.971	0.000
Median Housing Value	Residence	0.019	0.020	0.908	0.366
% Hispanic	Residence	-0.016	0.017	-0.928	0.356
% of jobs - White	Workplace	0.007	0.018	0.372	0.711
% of jobs - no college degree	Workplace	-0.052	0.019	-2.775	0.007

Therefore, we dropped *% of jobs - with college degree*. The second, related issue, is the impact of confounding variables - independent variables that are both associated with another independent variable and the dependent variable (ridership change). Therefore, to craft a parsimonious model we adopted a two-step procedure. First, we ran a simple linear regression analysis between each of the remaining independent variables and identified four variables with a P-value less than 0.05, which we identified as potentially statistically significant variables - *median housing value* (P-value: 0.000), *% Hispanic* (P-value: 0.033), *% of jobs - no college degree* (P-value: 0.000), *% of jobs - White* (P-value: 0.037).

The four potentially significant independent variables were used in the multi-variable OLS model presented in Table 4. All independent variables were Z-score standardized so that the magnitude of coefficients can be directly compared and the dependant variable was represented as a fraction. The model had a relatively moderate R^2 of 0.221 and adjusted R^2 of 0.184. Its important to note that this model does not aim to be a comprehensive predictive model, the purpose is to identify statistically significant independent variables to guide transit agencies as they study changes in ridership patterns due to the COVID-19 pandemic. With this in mind, we found that the percentage of jobs in a census tract held by workers without a college degree had the largest negative coefficient and was the only statistically significant variable (P-value less than 0.01). The large change in P-value for the other three variables in the multiple linear regression model compared to their simple regression models indicates that *median housing value*, *% Hispanic* and *% of jobs - White* are not significant when the variable *% of jobs - no college degree* is taken into account.

Paratransit usage and rider behavior in Nashville

Overall, there was a 66% decline in paratransit demand between April 28, 2020 to May 11, 2020 compared to a 2019 baseline in Nashville. As shown in Figure 9, there was an average decrease in paratransit demand of between 60% and 71% on weekdays, a decrease of 54% on Saturdays and an 86% average decrease on Sundays. The distribution of ridership demand compared to a 2019 baseline is provided in Figure 10. The largest decreases in demand were during morning rush, where there was an 81% decline from 7AM to 9AM and in the afternoon where there was also an 81% decrease in demand from 3PM to 4PM.

While there was ridership decline across all hours of the day, during COVID-19, paratransit demand was highest between 10AM and 12PM where peak demand in the 2019 baseline was between 3PM and 4PM, with a significant amount of demand during morning rush from 7AM-

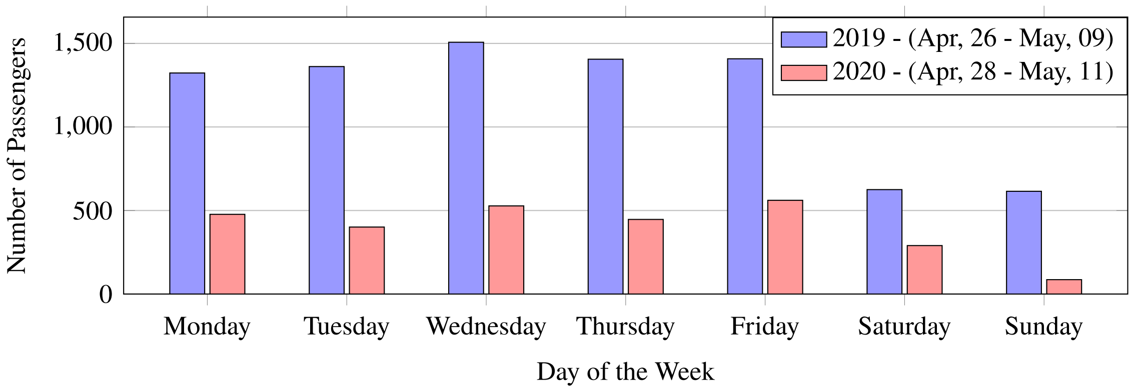


FIGURE 9 : Mean ridership by day of the week in paratransit services in Nashville between April 28, 2020 to May 9, 2020 compared to 2019.

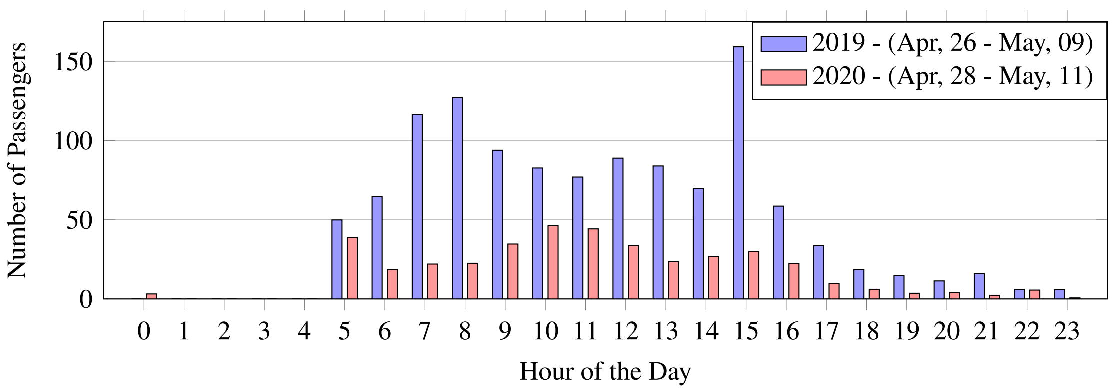
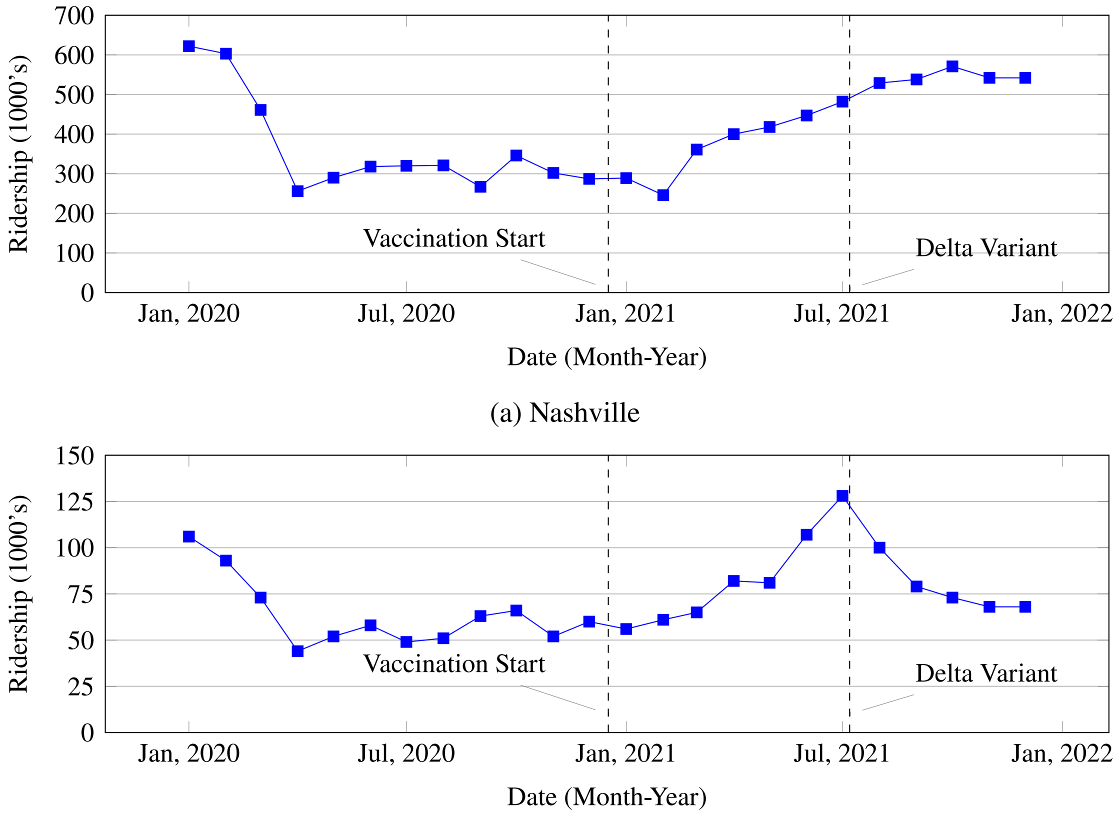


FIGURE 10 : Mean ridership based on hour of day in paratransit services in Nashville between April 28, 2020 to May 9, 2020 compared to 2019.

9AM. This indicates a potential shift in rider behavior towards requesting rides in the middle of the day. Additionally, unlike fixed-line bus transit, paratransit service was not restricted during the duration of this study. Therefore, decreased ridership in paratransit was directly from reduced demand. The temporal distribution of changes in ridership for paratransit in Nashville are similar our findings regarding the temporal distribution of changes in fixed-line bus transit in Figure 4a and Figure 5a.

TRANSIT RIDERSHIP PATTERNS EXTENDED

The ridership data available to us spanned January 1, 2020 to July 1, 2020. The extent of this work is therefore focused on the early portion of the COVID-19 pandemic. To provide a high-level overview of ridership trends since the initial submission of this work, we provide the monthly ridership for Nashville and Chattanooga from January 1, 2020 to January 1, 2022 in Figure 11. Ridership as presented in Figure 11 is derived from Automated Passenger Counter (APC) data available to us at the monthly level. Through discussions with the transit agencies at Nashville and Chattanooga, the APC data is not as reliable the farebox ridership data used in the preceding sections of this work. This is largely due to the fact that farebox data is collected directly from payment or by the driver as passengers enter the bus and is expected to be operational on all buses.



(a) Nashville

(b) Chattanooga

FIGURE 11 : APC monthly ridership for Nashville (a) and Chattanooga (b) between January 1, 2020 to January 1, 2022. December 17, 2020 is the date of the first vaccinations administered in Tennessee [34] and July 7, 2021 is the date in which the CDC recognized Delta as the dominant COVID-19 variant in the United States [35].

However, due to on-going maintenance issues with APC devices, it is possible for buses to operate with broken or malfunctioning APC devices. Therefore Figure 11 is included to provide additional context as to how trends have evolved over the course of the COVID-19 pandemic at a high level.

Both cities appeared to see a second recovery starting in early January 2021, which is shortly after the first vaccinations are administered in Tennessee on December 17, 2020. As noted in Figure 11, the Centers for Disease Control (CDC) recognized Delta as the dominant COVID-19 variant in the United States on July 7, 2021 [35]. An interesting observation is that transit ridership in Chattanooga started to decline after July 7, 2021, however Nashville's transit ridership continued to recover to near pre-pandemic levels.

DISCUSSION AND RECOMMENDATIONS FOR TRANSIT AGENCIES

We now present the key takeaways from this work. First, Both cities saw similar patterns in ridership decline despite the fact that Nashville and Chattanooga had cut vehicle trips by differing amounts. Additionally, the initial decline in ridership occurred well before vehicle trips were reduced in either city. This indicates that other factors influenced rider behavior outside of reductions in vehicle trips. Second, The largest declines in ridership were on weekdays during morning and evening commute times, indicating a potential persistent shift towards alternative work options or possibly a shift to personal vehicles. However, mobility patterns in Chattanooga indicates that foot traffic recovered to a greater degree than transit ridership, adding weight to the idea that commuters in particular may have shifted to personal vehicles. Third, we see that spatially, there is wide variance in ridership between census tracts which can be correlated with socio-economic characteristics of these areas. Our model shows that on aggregate (per census tract), areas with a high concentration of jobs held by workers without a college degree maintained higher transit ridership. Fourth, we find that despite the fact that paratransit was not restricted in supply, the temporal distribution of changes in paratransit ridership in Nashville are similar to ridership patterns in fixed-line transit.

Cities should be aware that transit usage patterns have changed as more high-income and college educated workers are able to work remotely or switch to personal vehicles to travel to work. As restrictions from COVID-19 are loosened, it is important to continue monitoring these patterns. In the context of this work, it is important for agencies to prioritize areas with a high concentration of jobs for low-income workers and workers without a college degree. If high-income workers continue to work remotely, switch to a hybrid schedule, or switch to personal vehicles, it is not only more equitable to prioritize low-income regions of urban areas but can become more economical as these areas begin to comprise of a greater share of the overall transit riders in the city.

THREATS TO VALIDITY

One limitation of this work is that it is focused only on two cities, both in Tennessee. Government restrictions vary greatly throughout the United States not only at the state level but at the city level. Even in this study Nashville Metro, the local government of Nashville and Davidson County, systematically enforced restrictions that differ from the Tennessee state restrictions under which Chattanooga was regulated. While Nashville has followed an outlined four stage opening plan, these stages many have different restrictions compared to other cities and states. Additionally while Nashville had recently moved to a more open stage three in late June it reverted back to stage two by July 4, 2020. However, we did not find that mixed messaging regarding social distancing in late June had a major impact on ridership demand.

Secondly, public transit entails confining passengers to an enclosed space whether social distancing is implemented or not. To date, there is no known mass transmission of COVID-19 in Nashville or Chattanooga that originated on public transit. A well publicized case such as this would most certainly have a negative impact on ridership. Historically mass transit can be a source of influenza and coronavirus transmission [7] however preliminary findings related to COVID-19 indicate that fears of public transit may be exaggerated [12]. Regardless it is imperative that transit agencies monitor social distancing and put in place adequate sanitation safeguards.

CONCLUSION

In this work we presented a data-driven analysis of the impact of COVID-19 on ridership in Nashville and Chattanooga, TN. We investigated the impact of reductions in vehicle trips on ridership and performed a spatio-temporal analysis of changes in fixed-line bus usage. Additionally, we presented a socio-economic analysis of transit ridership decline and presented our recommendations for transit agencies as regulations related to COVID-19 are lifted. Lastly, we showed that paratransit operations were impacted by COVID-19 in similar ways as fixed-line bus transit.

Future work includes developing low cost image processing methods for ensuring social distancing on public transit. We also plan on using the analysis in this work to set the ground for agent-based simulation and modeling to predict ridership behavior as the COVID-19 pandemic continues to unfold, and to help transit agencies better adapt to future sudden systemic changes in ridership demand dynamics.

ACKNOWLEDGMENT

This work was supported in part by National Science Foundation through award numbers 1952011, 2029950 and 2029952. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

AUTHOR CONTRIBUTIONS

M. Wilbur and A. Ayman provided technical guidance and management for the research, helped run data analyses, and helped write the manuscript. A. Sivagnanam and A. Ouyang, helped with data processing, ran analyses and helped write the manuscript. V. Poon helped with data processing and ran analyses. R. Kabir ran analyses and A. Vadali helped with literature review. P. Pugliese and D. Freudberg helped with data collection and provided technical guidance. A. Laszka and A. Dubey supervised the research and assisted with the manuscript writing.

References

[1] World Health Organization. Who pandemic announcement. `https://www.who.int/news-room/detail/29-06-2020-covidtimeline`.

[2] Jingqin Gao, Jingxing Wang, Zilin Bian, Suzana Duran Bernardes, Yanyan Chen, Abhinav Bhattacharyya, Siva Soorya Muruga Thambiran, Kaan Ozbay, Shri Iyer, and Xuegang Jeff Ban. The effects of the COVID-19 pandemic on transportation systems in New York City and Seattle, USA, May 2020.

[3] Daniel Baldwin Hess and Peter A Lombardi. Governmental subsidies for public transit: History, current issues, and recent evidence. *Public works management & policy*, 10(2):138–156, 2005.

[4] Anne E Brown. Car-less or car-free? socioeconomic and mobility differences among zero-car households. *Transport Policy*, 60:152–159, 2017.

[5] Danielle Taylor. Americans with disabilities: 2014. `https://www.census.gov/content/dam/Census/library/publications/2018/demo/p70-152.pdf`, November 2018.

[6] Phuong Nguyen-Hoang and Ryan Yeung. What is paratransit worth? *Transportation research part A: policy and practice*, 44(10):841–853, 2010.

[7] Annie Browne, Sacha St-Onge Ahmad, Charles R Beck, and Jonathan S Nguyen-Van-Tam. The roles of transportation and transportation hubs in the propagation of influenza and coronaviruses: a systematic review. *Journal of Travel Medicine*, 23(1):tav002, 2016.

[8] Jason R Andrews, Carl Morrow, and Robin Wood. Modeling the role of public transportation in sustaining tuberculosis transmission in South Africa. *American Journal of Epidemiology*, 177(6):556–561, 2013.

[9] Fang Zhao, Thomas Gustafson, et al. Transportation needs of disadvantaged populations: where, when, and how? Technical report, United States Federal Transit Administration, 2013.

[10] Andras Bota, L Gardner, and Alireza Khani. Modeling the spread of infection in public transit networks: A decision-support tool for outbreak planning and control. In *Transportation Research Board 96th Annual Meeting*, 2017.

[11] Matteo Chinazzi, Jessica T Davis, Marco Ajelli, Corrado Gioannini, Maria Litvinova, Stefano Merler, Ana Pastore y Piontti, Kunpeng Mu, Luca Rossi, Kaiyuan Sun, et al. The effect of travel restrictions on the spread of the 2019 novel coronavirus (covid-19) outbreak. *Science*, 368(6489):395–400, 2020.

[12] The Atlantic. Fear of public transit got ahead of the evidence. `https://www.theatlantic.com/ideas/archive/2020/06/fear-transit-bad-cities/612979/`, June 2020.

[13] Erik Jenelius and Matej Cebecauer. Impacts of covid-19 on public transport ridership in sweden: Analysis of ticket validations, sales and passenger counts. *Transportation Research Interdisciplinary Perspectives*, 8:100242, 2020.

[14] Alfonso Orro, Margarita Novales, Ángel Monteagudo, José-Benito Pérez-López, and Miguel R Bugarín. Impact on city bus transit services of the covid–19 lockdown and return to the new normal: The case of a coruña (spain). *Sustainability*, 12(17):7206, 2020.

[15] Alfredo Aloi, Borja Alonso, Juan Benavente, Rubén Cordera, Eneko Echániz, Felipe González, Claudio Ladisa, Raquel Lezama-Romanelli, Álvaro López-Parra, Vittorio Mazzei, et al. Effects of the covid-19 lockdown on urban mobility: Empirical evidence from the city of santander (spain). *Sustainability*, 12(9):3870, 2020.

[16] Jingqin Gao, Suzana Duran Bernardes, and Zilin Bian. Initial impacts of COVID-19 on transportation systems: A case study of the U.S. epicenter, the New York Metropolitan Area, April 2020.

[17] Yue Hu, William Barbour, Samitha Samaranayake, and Dan Work. Impacts of COVID-19 mode shift on road traffic. *arXiv preprint arXiv:2005.01610*, 2020.

[18] João Filipe Teixeira and Miguel Lopes. The link between bike sharing and subway use during the covid-19 pandemic: The case-study of new york's citi bike. *Transportation Research Interdisciplinary Perspectives*, 6:100166, 2020.

[19] Genevieve Giuliano and Susan Hanson. *The Geography of Urban Transportation*. Guilford Publications, 2017.

[20] Rick Grahn, Chris Hendrickson, Zhen Sean Qian, and H Scott Matthews. Socioeconomic and usage characteristics of public transit riders in the united states. Technical report, 2019.

[21] American Public Transportation Association. Who rides public transportation. `https://www.apta.com/wp-content/uploads/Resources/resources/reportsandpublications/Documents/APTA-Who-Rides-Public-Transportation-2017.pdf`.

[22] Kevin J Flannelly and Malcolm S McLeod. A multivariate analysis of socioeconomic and attitudinal factors predicting commuters' mode of travel. *Bulletin of the Psychonomic Society*, 27(1):64–66, 1989.

[23] K Mohamed, Etienne Côme, Johanna Baro, and Latifa Oukhellou. Understanding passenger patterns in public transit through smart card and socioeconomic data. *UrbComp,(Seattle, WA, USA)*, 2014.

[24] Jessica Murray. A systems analysis of access-a-ride, new york city's paratransit service. *Journal of Transport & Health*, 6:177–186, 2017.

[25] ViriCiti. Viriciti electric and non-electric fleet management. https://viriciti.com/.

[26] United States Government. United states census bureau. https://www.census.gov/.

[27] ProximityOne. Proximityone. http://proximityone.com/.

[28] United States Census Bureau. Longitudinal employer-household dynamics origin-destination employment statistics (lodes). https://lehd.ces.census.gov/data/.

[29] SafeGraph. Neighborhood patterns: Foot traffic insights by census block group. https://www.safegraph.com/neighborhood-patterns.

[30] The New York Times. Coronavirus in the u.s.: Latest map and case count. https://www.nytimes.com/interactive/2020/us/coronavirus-us-cases.html.

[31] Tennessee Office of the Governor. Public health orders. https://www.tn.gov/governor/covid-19/covid19timeline.html.

[32] Nashville Metro. Public health orders. https://www.asafenashville.org/public-health-orders/.

[33] USA Today. What we know wednesday about victims of the tennessee tornadoes and recovery efforts. https://www.usatoday.com/story/news/nation/2020/03/04/nashville-tornadoes-what-we-know-deaths-damage-path/4950396002/, March 2020.

[34] Tennessee covid-19 vaccination reporting. https://covid19.tn.gov/data/dashboards/, February 2022.

[35] Covid data tracker. https://covid.cdc.gov/covid-data-tracker, February 2022.