Transportation Research Interdisciplinary Perspectives 11 (2021) 100417

Contents lists available at ScienceDirect

Transportation Research Interdisciplinary Perspectives

journal homepage: www.sciencedirect.com/journal/transportation-research-interdisciplinary-perspectives

# Covid-19 and its effect on trip mode and destination decisions of transit riders: Experience from Ohio

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ARTICLE INFO

Keywords:
COVID-19
Public transit
Travel behavior
Trip mode

ABSTRACT

This research addresses travel patterns including trip mode and destination before and during the SARS-CoV-2 (COVID-19) pandemic. The team collected surveys from 1081 transit riders in Ohio. Shopping and work trips dropped the least (11–19%) while social visits and worship trips were reduced the most (49–61%). Bus, personal car use and paratransit dropped the least, while walking and ride share dropped the most.

Regression analysis revealed that female, married, children at home, higher income, and areas with high COVID infection rates had the largest decreases in trips. Being unbanked and being employed (including while working from home) saw stable or increased trips. Females and those with children felt less connected to the community, but unbanked people did not. Respondents likelier to fear catching COVID were female, nonwhite, have kids, older, and with highest incomes, but being employed or having a driver's license was not associated with increased fear.

## Introduction

The emergence and worldwide spread of SARS-CoV-2 (COVID-19, or COVID) in early 2020 led to dramatic behavioral changes in nearly all facets of life. This was prevalent in daily travel activities and public transit usage. The effects of the pandemic did not affect all socioeconomic groups equally, however, "essential" workers, who are often lower income, were less be able to work from home. This research looks to untangle the effects of the COVID pandemic on transportation use in Ohio to further investigate the influence of varying factors on changes to transit riders' travel behavior, both with respect to destination and modal choices, as well as trip frequency.

The transit surveys that underlie this research were collected in the third wave of COVID in Ohio. Fig. 1 shows these COVID-19 statistical data over a 54-week period from January 2020 to January 2021[1].

The pandemic is associated with behavioral changes that contributed to decreases in transit ridership of 50–70% compared to the equivalent time period in 2019. In response to the pandemic, some transit systems stopped collecting fares and eliminated front door boarding, meaning passengers could only board via the back doors. Transit systems also put in dividers, increased cleaning, reduced vehicle capacity, and mandated the masks. The pandemic has also furthered the push toward contactless fare media, most notably now as a mitigation tool to reduce risks of transmission. Percent changes in transit ridership from 2019 to 2020 for each of the Ohio transit agencies in this study, as well as for the United States overall, are displayed in Fig. 2.[2]

Our research falls within the context of a larger grant on innovative transportation payment technology (EZfare card). The research team collected 1081 surveys in late 2020 and early 2021 from transit riders from four agencies in Ohio: SARTA (Canton), Laketran (suburb of Cleveland), METRO RTA (Akron) and SORTA (Cincinnati).

The survey asked about trip destinations and travel modes before and during COVID. In addition to travel outcomes, the online survey also inquired about perceived social well-being, concerns about COVID, and respondent demographics.

We also conducted regression analysis using a data set of 550–850 qualified responses, depending on the model. We had three separate dependent variables that we wished to explain:

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[1] https://coronavirus.ohio.gov/wps/portal/gov/covid-19/dashboards

[2] The pre-pandemic values for all agencies are derived from actual ridership figures reported by the transit agencies through February 2020. Ridership during the pandemic for all agencies except SARTA was estimated from a statistical model based on measures of Transit app usage, and does not represent actual reported ridership counts (https://transitapp.com/apta). All ridership statistics for SARTA were calculated from actual ridership before and throughout the pandemic.

https://doi.org/10.1016/j.trip.2021.100417
Received 15 March 2021; Received in revised form 8 June 2021; Accepted 18 June 2021
Available online 7 July 2021

- What factors are associated with the reduction in trips in the week prior to the survey compared to pre-COVID activity?
- Which respondents felt that their connection to their community was reduced?
- Which respondents were fearful of contracting COVID-19 on public transportation?

The factors potentially explaining these outcomes (independent variables) are demographic characteristics of the respondents, other rider-specific travel information, as well as general economic factors and local weekly new COVID cases.

The order of this paper is as follows: a literature review of pandemics and public transportation, data-gathering methodology, and descriptive statistics on findings of the four transit agencies. Next, we bring forth the regression analysis methodology and findings. The paper ends with conclusions and policy recommendations.

## Literature review

This literature section addresses the relationship between public transit and a number of factors, including the current COVID pandemic, prior pandemics around the world, a breakdown of which socioeconomic groups appear to have been affected, and the emergence of touchless payment systems in the context of reducing the risk of contracting COVID from surfaces.

Transit agencies worldwide have witnessed reductions to ridership from COVID (Almof, 2020; Arellana et al., 2020; Barbieri et al., 2021; Bucsky, 2020; Liu et al., 2020; Orro et al., 2020). While the overall effect of the pandemic was to suppress transit usage at the aggregate, recent research has suggested that these effects were not evenly distributed across different socioeconomic and occupational characteristics (Almof et al., 2020; Liu et al., 2020; Shamshiripour et al., 2020). Recent findings from Hu and Chen (2021) has pointed to individuals of lower-income, less-education, and people of color as most likely to continue using public transit during the pandemic. While the number of studies focusing on pandemics and transportation were, until recently, limited, the global COVID outbreak has shifted the emphasis towards research aimed at understanding the public's response to pandemics. This recent influx of literature, along with a handful of previous studies, originate from a variety of countries worldwide and investigate a wide range of topics.

Related research prior to COVID was mainly concerned with the 2003 SARS, 2009 H1N1, and the 2015 MERS outbreaks. Following the onset of the SARS epidemic, Lau et al. (2003) surveyed 1397 Hong Kong residents to evaluate the perceptions and behaviors of the public during the first two stages of the epidemic. The authors found that 48% of respondents feared being infected in public places, 51% perceived the risk of SARS transmission via public transportation usage as 'high' or 'very high,' and 24% avoided using public transportation as a preventive measure.

Also interested in the public's perception and response to SARS and influenza pandemics, Sadique et al. (2007) surveyed 3436 respondents across 7 countries in Europe and Asia to identify the public's perceived risk of certain locations and possible behavioral modifications when facing a global influenza pandemic. The authors found that 54% of respondents identified public transportation as the riskiest place, along with three-quarters stating they would avoid using transit during a pandemic.

A final examination of the SARS outbreak comes from Wang and Thiel (2014), who analyzed daily underground transit ridership data and SARS cases in Taipei City, Taiwan. They identified two relationships between transit ridership and reported SARS cases: first, a quick public response to new reported cases that led to a precipitous decline in ridership, followed by a gradual increase in ridership as the pandemic faded. This is reflected in a loss of around half the Taipei City daily ridership during the peak of the pandemic, as well as the excess of four months needed for ridership to return to pre-pandemic levels following the last publicized case of SARS.

Shifting to the 2009 H1N1 influenza pandemic, SteelFisher et al. (2010) reviewed 20 U.S. public opinion polls to examine the public's behavioral changes over three periods corresponding to the time before a vaccine was available through widespread availability. The authors found that in the early stages of the outbreak, 20% of respondents had reduced personal contact with individuals outside of their household as much as possible and 12% had limited their use of public transportation.

Utilizing individual smart card transaction data from public transit

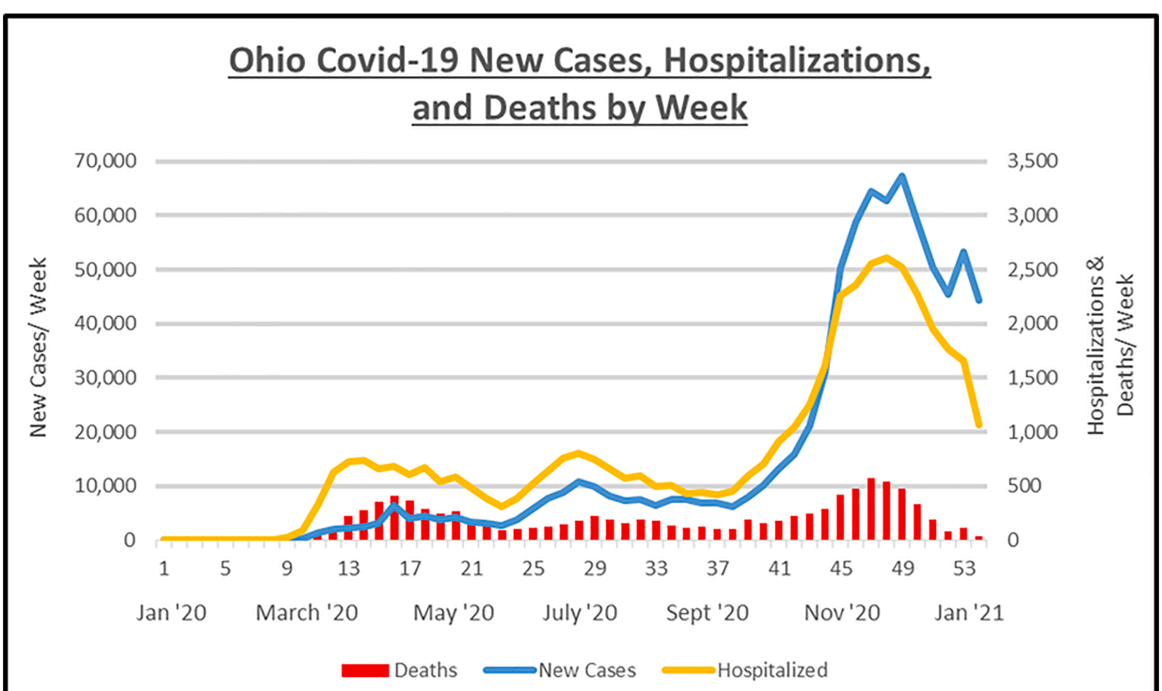


**Fig. 1.** New COVID-19 cases, hospitalizations, and deaths per week in Ohio from January 2020-January 2021.

and average land values, Kim et al. (2017) analyzed changes in transit ridership in Seoul, South Korea during the MERS epidemic in 2015 through the lenses of socioeconomic status and life stability. In the three weeks following the MERS outbreak, the authors found the number of trips taken on public transit and the number of individuals traveling on public transit decreased by 12% and 11%, respectively, with higher land values (the proxy for socioeconomic status) associated with a greater reduction in trip frequency.

The recent COVID pandemic has spurred a wave of new research into pandemics and public transportation, with contributions originating from countries and regions across the world. Hu and Chen (2021) used 20 years of daily transit ridership data from Chicago (USA) to infer the impact of COVID on ridership, as well as how land-use and demographics characteristics explain ridership declines. Results revealed an average drop in ridership of 72%, with white, higher-educated, and higher-income individuals associated with greater decreases in ridership. Conversely, areas with more jobs in transportation, trade, and the utility sector expressed smaller declines.

Arellana et al. (2020) analyzed government and secondary data from metro areas in Columbia and observed an overall reduction in demand for public transportation systems between 80 and 96% of pre-pandemic levels, as well as an 80% reduction in trips to retail shopping, recreational activities, and parks, and a 60% reduction in trips to places of work, grocery shopping, and pharmacies. Additionally, reductions in congestion levels were found to be greater than the reductions in transit demand, suggesting trip reductions for public transit was less than that of private vehicles.

Orro et al. (2020) analyzed data from transit records and smart cards in A Coruña, Spain to ascertain the impact on bus transit services during the lockdown period and the 'new normal' (the period following). The authors found an initial 84–92% reduction in bus transit demand from the baseline levels which remained throughout the lockdown, increasing steadily during the phased reopening, and finally topping out at levels 41–51% below the baseline. It was also found that during the lockdown malls and universities saw almost all transit activity cease, while hospitals and places where essential purchases took place maintained activity levels between 15 and 21% of pre-COVID.

Utilizing smart card data and neighborhood-level demographic data from Stockholm County, Sweden to explain the decline in public transportation and change in travel behaviors through socioeconomic factors, Almlöf et al. (2020) found that while the overall decline in public transit trips was 75%, those who had the means to stop using transit were much more likely to do so than those with lower socioeconomic status. While all cluster groups showed large declines in ridership, the decline varied significantly from the 'impoverished' cluster's decline of 61%, to the 'working class' and 'rural' clusters' declines of 72% and 74%, respectively, up to the affluent 'central' and 'garden suburb' clusters' declines of 78% and 77%. With regards to different occupations, those employed in entertainment or healthcare were more likely to continue using public transit, while those employed in retail, service, education, hotel, or restaurant professions were more likely to stop using transit.

Bucsky (2020) analyzed public transit ridership data from the Budapest (Hungary) Centre for Transport during the initial month of the outbreak, as well as changes to modal share from the 2018 baseline. The author found an 80% reduction in public transit demand from the first half of March to the second, and a 57% reduction for the second half of March when compared to the baseline levels. With respect to modal share, public transportation's share dropped from the baseline of 43% to 18% during the second half of the month.

In order to understand the changes to individual travel behavior that will transpire following COVID, along with the environmental impacts of those changes, Sui et al. (2020) analyzed survey, smart card, and GPS data from residents of Qingdao, China who use the bus at least twice per day. Results indicated that 56% of respondents will decrease their usage of buses following the pandemic, accompanied with a reported 43% increase in their usage of private vehicles. Of those that reported a shift away from public transportation, 78% reported the reason as concern over a greater risk of infection on crowded buses.

In Punjab Province, Pakistan, Haq et al. (2020) evaluated the public's knowledge of COVID, as well as their behavioral responses and preventive measures taken to guard themselves from infection. The authors found that, altogether, 61% of respondents considered public transportation as the riskiest place for COVID infection, with 95% of urban and 87% of rural residents reporting they have avoided public

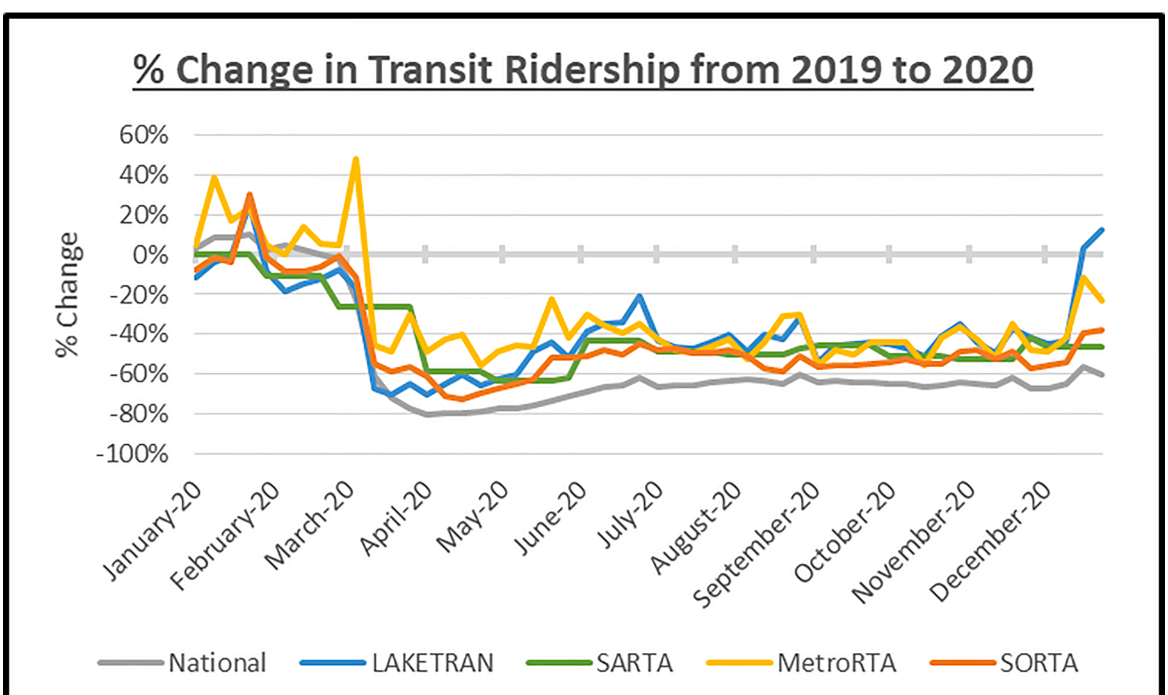


**Fig. 2.** A comparison of the national and local (Laketran, SARTA, MetroRTA, and SORTA agencies) in the percent change in transit ridership from January 2020-December 2020.

transportation during the pandemic. In order to better understand the societal level effects of the COVID pandemic in Turkey, Bostan et al. (2020)'s study found that of the respondents, 54% 'agree' or 'totally agree' that they have adjusted their 'whole life' according to the pandemic, 93% 'agree' or 'totally agree' that they practice social distancing as a protection against infection, and 88% 'agree' or 'totally agree' that they stay home as a preventative response to the pandemic.

Using data from ten countries on six continents, Barbieri et al. (2021) examined individual mobility patterns across a variety of transport modes before and during the COVID pandemic and corresponding mobility restrictions. Across all countries, use of all transport modes decrease significantly, albeit to varying extents for each. The main socioeconomic factors contributing to the change in travel behavior and perceptions were found to be income inequality and the reported death toll due to COVID per 100,000 residents.

Pivoting to recent research from the United States, Liu et al. (2020) analyzed data from 113 public transit systems using transit navigation queries from Transit App as a proxy for ridership demand. The authors found that while the average decrease in ridership demand across all transit systems was 73%, demand levels and reductions were not equal across all communities. Thus, communities with a higher proportion of essential workers and vulnerable populations maintained higher levels of transit demand, while communities with a higher proportion of non-physical occupations experienced greater reductions in transit demand.

In the Chicago metro area, Shamshiripour et al. (2020) investigated the public's daily travel behaviors, habits, and perceptions before and during the COVID pandemic, as well as expectations going forward. The authors found that public transit, taxi, and ride-hailing services were viewed as the three highest risk modes of transportation, with 78% of respondents indicating they associate public transit with 'high' or 'extremely high' risk. The effects of the pandemic were also found to disproportionately affect part-time workers, as compared to full-time workers, with part-time workers losing their jobs at a nearly 3.5 times higher rate than full-time workers, as well as being temporarily laid off at a 2.5 times higher rate.

Early in the COVID pandemic (March and April 2020) riders were avoiding public transportation because of concerns of possible exposure to COVID (Haq et al., 2020; Shamshiripour et al., 2020). While studies have shown the public's perception of transit as a high-risk vector for the spread of COVID and other pathogens, recent studies have revealed a somewhat conflicting reality. Regarding the presence of COVID in public transportation vehicles, Di Carlo et al. (2020) found no evidence of the virus on either surfaces or the air within buses over a two-week period and more than 1,100 riders. Moreno et al. (2021), found that while

**Table 1**
A summary of the literature reivew related to pandemics and transportation.

| Authors | Year of Analysis | Pandemic | Location | Key Findings |
|---|---|---|---|---|
| Hu et al. | 2020 | COVID-19 | USA (Chicago) | Lower-income, less-educated, and people of color most likely to continue using public transit<br>Regions with more jobs in trade, transportation, and utility sectors presented smaller declines |
| Barbieri et al. | 2020 | COVID-19 | 10 Countries on 6 Continents | ·Main socioeconomic variables of change in travel behavior were income inequality and reported death toll due to COVID-19 per 100,000 inhabitants<br>Substantial reduction in the frequency of all types of trips and use of all modes |
| Shamshiripour et al. | 2020 | COVID-19 | USA (Chicago) | 78% perceive public transit as high or extremely high risk<br>·Part-time workers 3.4 times more likely to lose their job than those employed full-time |
| Liu et al. | 2020 | COVID-19 | USA | Average decrease in demand across transit systems was 73%<br>Communities with a higher proportion of essential workers & vulnerable populations maintained higher levels of demand<br>Communities with a higher proportion of non-physical occupations experienced greater reductions in demand |
| Bostan et al. | 2020 | COVID-19 | Turkey | 88% agree or totally agree that they stay home as a protection against COVID-19<br>54% agree or totally agree that they have adjusted their "whole life" according to the pandemic |
| Haq et al. | 2020 | COVID-19 | Pakistan (Punjab Province) | 61% consider public transit as the riskiest place for COVID-19 infection.<br>95% of urban and 87% of rural residents report avoiding public transit during COVID. |
| Siu et al. | 2020 | COVID-19 | China (Qingdao) | 56% of respondents indicate they will decrease their usage of buses following COVID-19<br>78% report the reason for shift away from public transit is concern of greater inflection risk in crowded buses |
| Bucsky et al. | 2020 | COVID-19 | Hungary (Budapest) | 25 percentage point decrease in public transit's modal share from baseline<br>Overall mobility was reduced by 57% for the second half of March (post outbreak) compared to previous year |
| Almlof et al. | 2020 | COVID-19 | Sweden (Stockholm County) | Overall public transit trips declined by 75%<br>Lower socioeconomic areas declined less than more affluent areas |
| Orro et al. | 2020 | COVID-19 | Spain (A Coruna) | Ridership by busline over the first 6 months of 2020 was 38%-56% lower than the first 6 months of 2019<br>During lockdown, malls and universities saw almost all activity cease, while hospitals and places for essential purchases stayed between 15% and 21% of pre-COVID levels |
| Arellana et al. | 2020 | COVID-19 | Columbia | 80% decline in trips to retail shopping, recreational activities, and parks<br>60% decline in trips to work, grocery stores, and pharmacies<br>Reductions in congestion were greater than the reductions in transit demand, suggesting trip reductions for public transit was less than that of private vehicles |
| Kim et al. | 2015 | MERS | South Korea (Seoul) | In 3 weeks following outbreak, 12% decline in public transit trips and 11% decline in individuals using public transit<br>Land price (proxy for socioeconomic status) had a high correlation with reduction in transit ridership, with higher land value associated with a greater reduction in trip frequency |
| SteelFisher et al. | 2009 | H1N1 | USA | 12% limited their use of public transit<br>16%-25% avoided places with large gatherings of people, like public transportation, malls, and sporting events |
| Wang | 2014 | SARS | Taiwan (Taipei City) | Around 50% loss of daily ridership during peak of pandemic<br>·134 days following the last announced case of SARS for ridership to return to pre-pandemic levels |
| Sadique et al. | 2005 | SARS | Europe and Asia | 54% identified public transportation as the riskiest place<br>·75% said they would avoid public transportation |
| Lau et al. | 2003 | SARS | China (Hong Kong) | 51% consider public transit as having high or very high risk of SARS transmission<br>24% overall avoiding public transportation as preventative behavior |

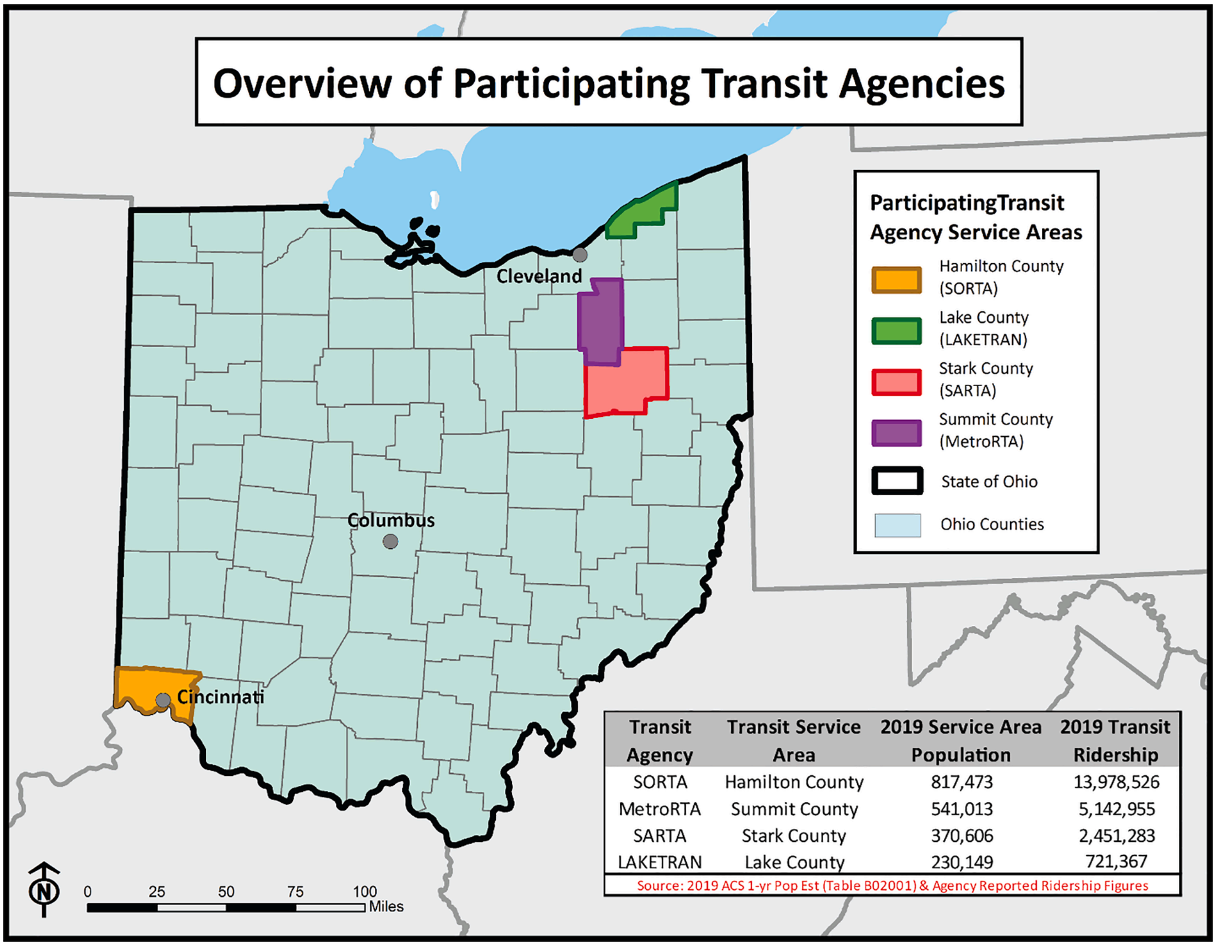


**Fig. 3.** A map of Ohio and the participating transit service areas, including their area population and ridership.

traces of the virus could be detected in some of the buses and trains sampled, the concentrations were fragmented and weak enough to be of little to no concern for infectivity. These findings would seem to give credence to the assertion that the precautions adopted on public transit are effective in reducing the risk of COVID transmission. The literature review is summarized in Table 1.

## Data collection

The data collection procedures produced 1,081 survey completions across four transit agencies within Ohio: the Stark Area Regional Transit Authority (SARTA), serving Stark County, Laketran, serving Lake County, METRO RTA, serving Summit County, and the Southwestern Ohio Regional Transit Authority (SORTA), serving Hamilton County. From this survey solicitation, 227 completed responses were elicited from SARTA riders, 254 from Laketran, 200 from Akron METRO RTA, and 400 from SORTA. Fig. 3 presents an overview of the participating transit agencies' service areas.

### *Survey procedures*

The survey was vetted by the Cleveland State University Institutional Review Board. Surveys were collected between October 2020 and January 2021, a period within the third wave of the COVID pandemic that included the largest increase in weekly new COVID cases and hospitalizations in Ohio (see Fig. 1, above). Nearly all surveys were collected over the internet, with approximately five percent contacted over the telephone. Respondents were invited to participate through a transit email list, over social media, and by postcards handed to passengers or on-site posters advertising the survey. While it is not possible to determine precise response rates, about 15% of the people who received the survey link clicked on it. Among the phone call group, the net response rate was about 20%.

Respondents were rewarded with a free transit pass of at least $20 for successful completion of the survey. For some of the transit agencies, the total number of responses to each survey was capped (METRO RTA at 200 and SORTA at 400). Thus, the sample is self-selected, and we acknowledge this is not a random sample.

### *Sample fit with the population*

Although this is not a random sample, our overall sample is generally a good fit with the underlying transit riders it is meant to represent. To show this, Table 2 provides a comparison of each of the four transit partners (ridership versus our sample) with twelve indicators. The figures on the right compare the overall representativeness of our sample with transit riders where data was available for both[3]. For the twelve comparison categories, the weighted differences in percentage was largely comparable: five categories (employed, unemployed, ages 65 and up, has valid driver's license, and no vehicle in the household) were

[3] Not all underlying transit ridership demographics, taken from on-board transit surveys (METRO RTA 2020, SARTA 2018, SORTA 2018, Laketran 2012), had all variables available. Comparisons, therefore, were made to the sample demographics when possible, and the survey sample was compared by transit agency, as well as overall. The number of transit agencies compared for each variable is shown within the ().

**Table 2**
A comparison of the survey population from each transit agency with the actual transit agency ridership.

| | MetroRTA | | SARTA | | Laketran | | SORTA | | Total | |
|---|---|---|---|---|---|---|---|---|---|---|
| Categories | Ridership | Sample | Ridership | Sample | Ridership | Sample | Ridership | Sample | Ridership | Comp. Sample |
| African American (4) | 53.4% | 33.0% | 40.0% | 37.0% | 15.2% | 19.3% | 62.3% | 45.0% | 44.9% | 35.1% |
| Female (4) | 43.3% | 53.5% | 53.0% | 62.1% | 54.4% | 57.1% | 51.6% | 56.8% | 51.0% | 57.4% |
| Household Income < $20 K (4) | 50.2% | 47.0% | 75.0% | 67.0% | 52.9% | 35.4% | 53.9% | 29.3% | 57.4% | 41.9% |
| Ages 25–44 (4) | 35.2% | 40.5% | 41.0% | 55.9% | 24.8% | 32.3% | 37.0% | 44.5% | 34.6% | 43.3% |
| Ages 45–64 (3) | 31.3% | 39.5% | NA | 25.1% | 36.1% | 42.5% | 30.5% | 42.5% | 32.4% | 41.8% |
| Ages 65 & up (3) | 7.2% | 8.5% | NA | 3.1% | 23.1% | 14.6% | 6.3% | 5.8% | 11.5% | 9.0% |
| Employed (3) | 63.9% | 59.5% | 60.0% | 46.7% | NA | 63.8% | 69.2% | 73.8% | 65.4% | 62.9% |
| Unemployed (3) | 32.4% | 12.0% | 14.0% | 20.3% | NA | 6.7% | 10.4% | 9.8% | 16.7% | 13.2% |
| No Vehicles in Household (3) | 68.2% | 64.0% | 75.0% | 80.2% | 37.0% | 38.6% | NA | 54.5% | 58.8% | 59.9% |
| Has Valid Driver's License (2) | 32.4% | 40.0% | 26.0% | 28.6% | NA | 52.8% | NA | 46.8% | 29.0% | 34.0% |
| Has a Cellphone (1) | NA | 95.0% | 92.0% | 98.2% | NA | 89.0% | NA | 97.3% | 92.0% | 98.2% |
| With a Mobility Impairing Disability (1) | NA | 31.0% | NA | 27.8% | 26.9% | 33.9% | NA | 21.3% | 26.9% | 33.9% |
| Sample Count | * | 200 | * | 227 | * | 254 | * | 400 | | |

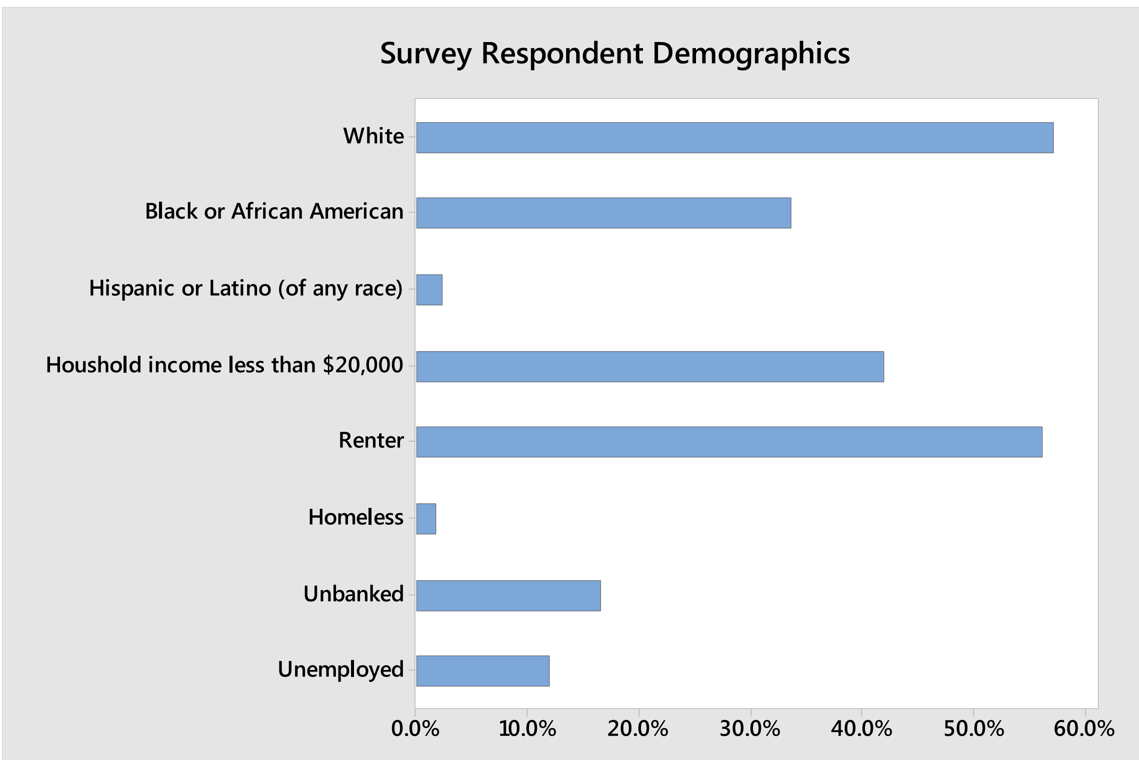


**Fig. 4.** The demographics of survey respondents.

within 5 percentage points, while six others were within ten percentage points (African-American, female, ages 25–44, ages 45–64, has a cell phone, and has a mobility impairing disability). Only one comparison category (income below $20,000) was outside this range at 15.5% off. Thus, our sample, although not random, is acceptably representative of the underlying transit rider population.

### Descriptive statistics of survey results

Survey participants were asked a series of questions that fell into the following broad categories: method of payment; weekly pre- and post-COVID travel behavior, including trip destination types and trip frequencies; satisfaction with the amount of time taken and the overall experience for all transportation modes used by respondents; quality of life, before and after the onset of COVID-19; and demographics, including characteristics such as gender, race, education, housing status, and household income. The data in this section include all 1,081 respondents.

Fig. 4 shows some of demographic characteristic for the survey respondents. The classification of race illustrated there follows the standards on race and ethnicity followed by the U.S. Census Bureau whereby the concept of race is separate from that of Hispanic origin.[4] Overall, 57.2% of survey respondents identified as White alone, not in combination with any other racial category, while 33.7% identified as Black or African American alone. Additionally, 2.3% of survey respondents identified as Hispanic or Latino.

Across all three agencies represented in the sample, 41.9% of respondents reported an annual household income of less than $20,000. Ohio's median household income, for reference, was $56,602 (in 2019

[4] https://www.census.gov/topics/population/race/about.html

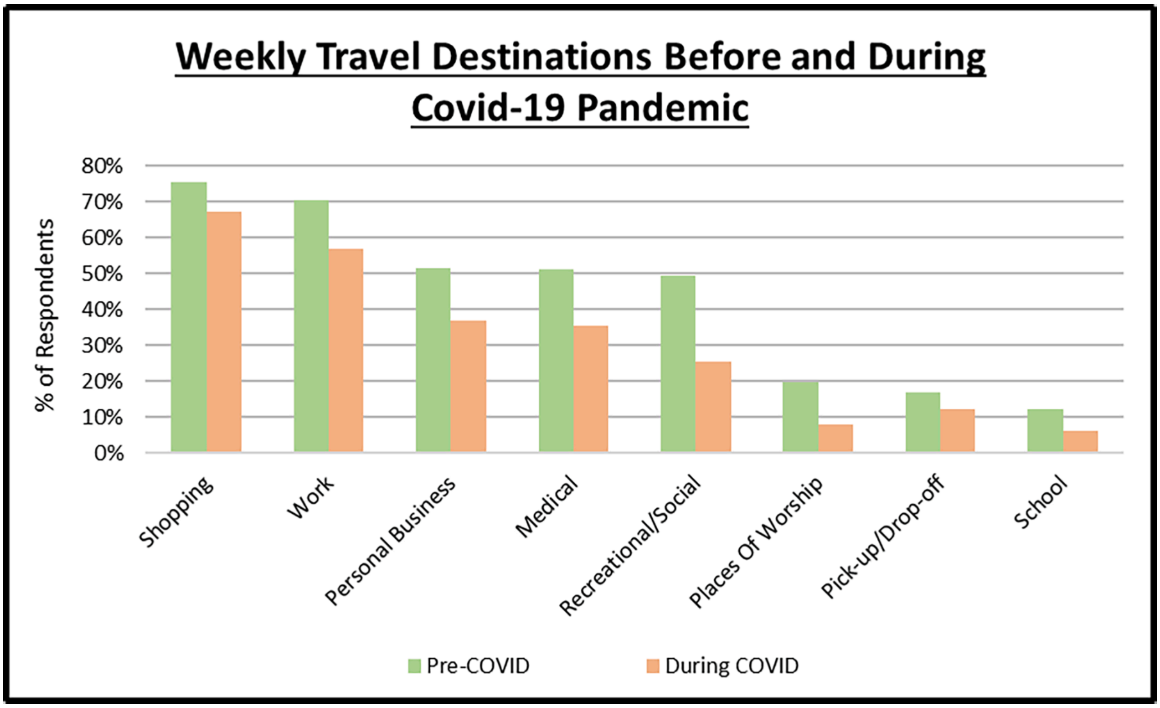


**Fig. 5.** A comparison of weekly travel destinations before versus during COVID-19.

**Table 3**
Changes in weekly travel destinations before versus during COVID-19.

| Travel Destination | Pre-COVID | | During COVID | | Change | |
|---|---|---|---|---|---|---|
| | Individuals | % of Sample | Individuals | % of Sample | Individuals | % |
| Shopping | 817 | 75.6% | 727 | 67.3% | −90 | −11.0% |
| Work | 761 | 70.4% | 613 | 56.7% | −148 | −19.4% |
| Personal Business | 557 | 51.5% | 399 | 36.9% | −158 | −28.4% |
| Medical | 553 | 51.2% | 383 | 35.4% | −170 | −30.7% |
| Recreational/Social | 535 | 49.5% | 275 | 25.4% | −260 | −48.6% |
| Places Of Worship | 214 | 19.8% | 84 | 7.8% | −130 | −60.7% |
| Pick-up/Drop-off | 182 | 16.8% | 131 | 12.1% | −51 | −28.0% |
| School | 132 | 12.2% | 67 | 6.2% | −65 | −49.2% |

dollars) according to the U.S. Census Bureau's vintage 2019 population estimates.[5] With regard to housing status, 56.1% of respondents identified themselves as renters while 1.8% of survey takers were homeless or living in a shelter.

The *unbanked* represented 16.6% of the respondents that were surveyed. Following household banking status categories established by the Federal Deposit Insurance Corporation, this means that they have neither a checking nor a savings account.[6] Additionally, 11.9% of respondents across all agencies were *unemployed* according to the federal government's classification system for assigning employment/unemployment status based on labor force activities.[7] This percentage of all respondents who were unemployed translates to an unemployment rate of 15.8% given the ratio of unemployed respondents to those who would qualify as being in the *labor force* (i.e. the sum of employed and unemployed individuals). Additionally, 24.4% of all respondents indicated that they were *not in the labor force* as they held no job (full-time, part-time, or temporary) and they were not actively looking for one.

*Pre-and during COVID travel patterns*

Survey respondents were asked about their weekly travel behaviors and, more specifically, whether they traveled to a selection of destination types during the week before they took the survey (during COVID) and during a typical week before the onset of the COVID pandemic. We trimmed our data set to account for possible inconsistencies within the survey instrument[8], and Fig. 5 and Table 3 illustrate the changes in individual's travel destinations.[9]

Overall, there was a decrease in the percentage of respondents who traveled to each destination type following the onset of COVID. However, individuals traveling to places of worship and for recreational or social activities saw the greatest decrease, with losses of 61% and 49% respectively. Conversely, the travel destinations that were least affected

[5] https://www.census.gov/quickfacts/OH
[6] https://economicinclusion.gov/glossary.html
[7] https://www.bls.gov/cps/cps_htgm.htm#info

[8] The survey instrument included a question concerning 1-way trips to "home;" however, following examination of the results, discrepancies were found in the answers given that would suggest the respondents did not fully understand this question and it was therefore removed from the analysis. It is the opinion of the authors that the remaining questions concerning travel destinations were understood by the survey respondents.

[9] Travel destination does not imply a specific mode of transportation, and respondents may have traveled to each destination by any mode, including but not limited to public transportation, private vehicle, walking, biking, etc.

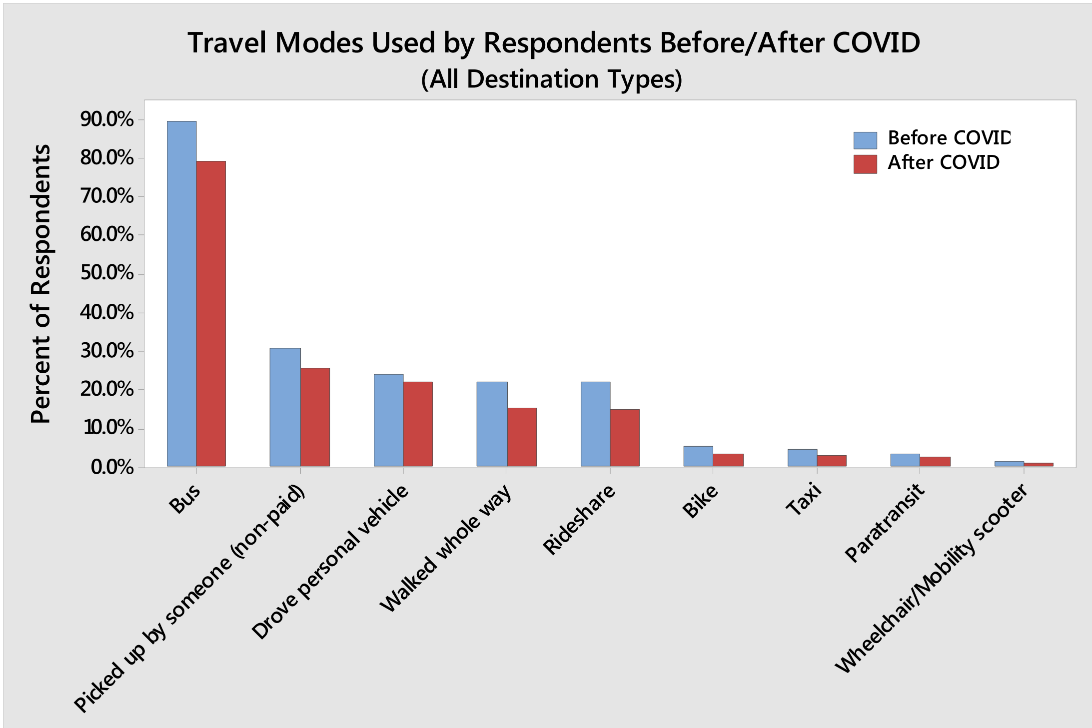


**Fig. 6.** The percentabe of respondents who traveled via a selection of typical travel modes before and during COVID-19.

by the onset of the pandemic were shopping and work, with decreases of 11% and 19% respectively. There was, however, some variation across the transit agencies, with noticeable differences in stated pre/during COVID travel behaviors for a few categories. For example, while the overall number of respondents who reported traveling for shopping decreased 8.3 percentage points after the onset of COVID, SARTA saw a comparative during-COVID increase of 0.4 percentage points for shopping among its survey respondents.

Survey respondents were also asked about their weekly travel behavior, both before and after the onset of COVID, with respect to the modes of transportation they used. Fig. 6 shows the percentage of respondents who traveled via a selection of common travel modes before and during the pandemic. Table 4 shows a cross tabulation of this modal shift with the most common trip destinations and the change in the number of passenger trips by destination-mode combination after the onset of COVID, where percent decreases of greater than 50% are emboldened in red. Large relative decreases were more frequently observed for ride-hailing/ridesharing services, and for walking the whole way to a destination.

Additional questions posed to respondents pertained to how frequently they traveled on a weekly basis before and after the onset of COVID. They were asked how many one-way trips they took to each destination type during the week prior to taking the survey, and how many one-way trips they made to each destination type during a typical week before the onset of COVID. Across all agencies, the mean number of weekly one-way trips per respondent for all transportation modes and destinations decreased from 15.9 trips before the onset of COVID, to 10.8 trips after COVID. This decrease in mean weekly travel, by agency, ranged from 3.1 to 6.3 fewer one-way trips per respondent after the onset of COVID.

### *Fear of catching COVID*

Survey takers were also asked how concerned they were about catching COVID-19, both in general and from other passengers when using public transit. Fig. 7 describes the levels of respondent concern with respect to catching COVID. Among the respondents surveyed, 45.5% were either moderately or extremely concerned about catching COVID in general, while 46.1% were either moderately or extremely concerned about catching COVID from other transit passengers. Conversely, 15.8% of respondents were not at all concerned about catching COVID in general, and 17.0% were not at all concerned about catching COVID from other transit passengers.

Respondents indicated some variation in their level of concern over catching COVID by method of transmission. For example, 26.2% of respondents were *extremely concerned* about catching COVID by breathing it in through the air, compared to 21.6% of respondents who expressed this sample level of concern over catching the virus from touching surfaces, a difference of 4.6%. Differences in level of concern over catching COVID by method of transmission did not seem as pronounced for lower levels of concern. For instance, 18.3% of respondents were *not at all concerned* about catching COVID from breathing it in, while 18.5% were concerned about catching the virus from touching surfaces. Thus, the potential benefits of a touchless payment system may appeal to a large percentage of riders, both in general, and for those with concern about touching surfaces.

Survey respondents also indicated variation in feelings of connectedness to their community after the onset of the COVID pandemic compared to before. When asked to express their current level of agreement/disagreement with the statement "I feel connected to my community," as well as to what extent they recalled agreeing/disagreeing with this statement before the onset of the pandemic, 74.8% indicated past agreement while 70.9% indicated present agreement, a decline of 3.9 percentage points. This was the largest absolute decrease in post-onset agreement among a series of quality-of-life statements presented to the respondents, which included: *I feel optimistic about the future*; *the conditions of my life are excellent*; and *I feel satisfied with my life*.

## Regression analysis

The regression component of this study seeks to answer the following questions:

**Table 4**
A cross tabulation of the modal shift with most common trip destinations nad change in number of passenger trips by destination mode.

| Destination/Mode | Work | | Shopping | | Medical Appt./Dr's Office | | Personal Business | | Recreational/Soc. Activities | |
|---|---|---|---|---|---|---|---|---|---|---|
| Bus | Pre- COVID | 666 | Pre- COVID | 552 | Pre- COVID | 364 | Pre- COVID | 354 | Pre- COVID | 328 |
| | Post- COVID | 503 | Post- COVID | 460 | Post- COVID | 245 | Post- COVID | 241 | Post- COVID | 150 |
| | % change | −24% | % change | −17% | % change | −33% | % change | −32% | % change | **−54%** |
| Walked whole way | Pre- COVID | 65 | Pre- COVID | 128 | Pre- COVID | 30 | Pre- COVID | 112 | Pre- COVID | 103 |
| | Post- COVID | 34 | Post- COVID | 78 | Post- COVID | 8 | Post- COVID | 49 | Post- COVID | 28 |
| | % change | −48% | % change | −39% | % change | **−73%** | % change | **−56%** | % change | **−73%** |
| Ride-hail/Rideshare | Pre- COVID | 118 | Pre- COVID | 98 | Pre- COVID | 77 | Pre- COVID | 54 | Pre- COVID | 101 |
| | Post- COVID | 72 | Post- COVID | 50 | Post- COVID | 23 | Post- COVID | 26 | Post- COVID | 19 |
| | % change | −39% | % change | −49% | % change | **−70%** | % change | **−52%** | % change | **−81%** |
| Drove Personal vehicle | Pre- COVID | 121 | Pre- COVID | 196 | Pre- COVID | 124 | Pre- COVID | 166 | Pre- COVID | 164 |
| | Post- COVID | 91 | Post- COVID | 158 | Post- COVID | 63 | Post- COVID | 109 | Post- COVID | 71 |
| | % change | −25% | % change | −19% | % change | −49% | % change | −34% | % change | **−57%** |
| Picked up/Dropped off (non-paid svc.) | Pre- COVID | 123 | Pre- COVID | 175 | Pre- COVID | 90 | Pre- COVID | 113 | Pre- COVID | 152 |
| | Post- COVID | 77 | Post- COVID | 130 | Post- COVID | 46 | Post- COVID | 73 | Post- COVID | 63 |
| | % change | −37% | % change | −26% | % change | −49% | % change | −35% | % change | **−59%** |

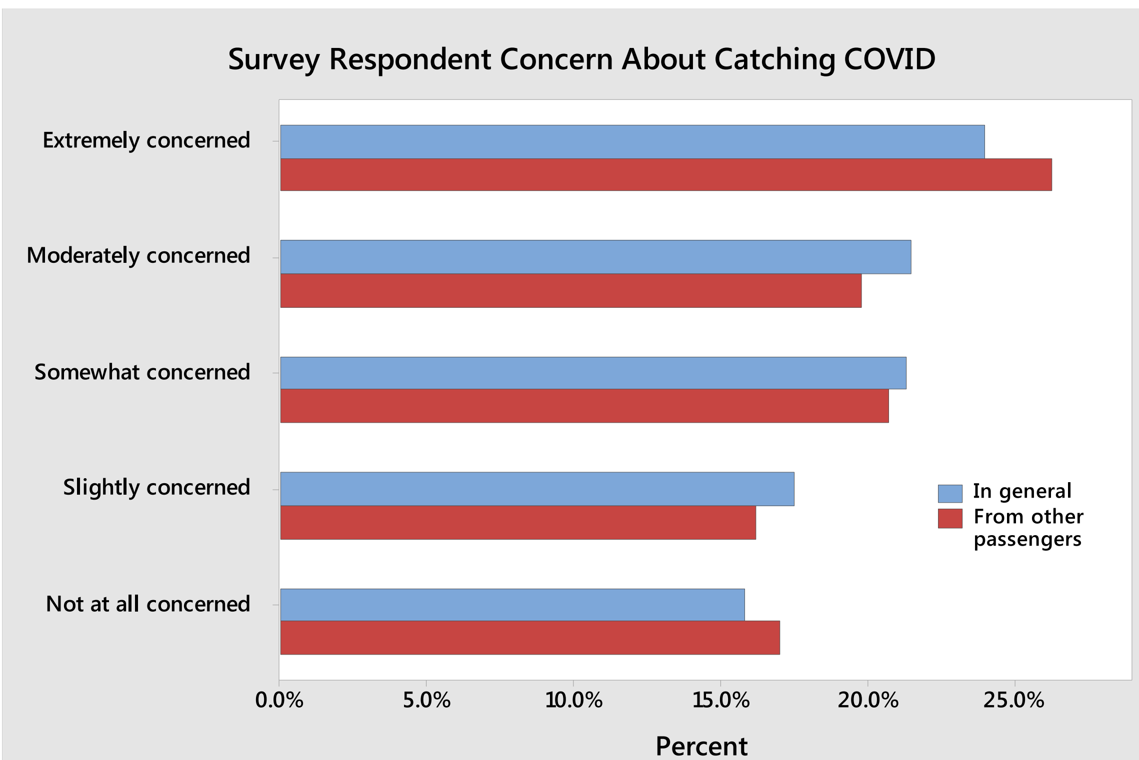


**Fig. 7.** The levels of respondent fear of catching COVID-19.

1. Who is experiencing the greatest change in frequency of weekly trips before and during COVID?
2. Who is experiencing change in feeling of connectivity?
3. Who among transit riders is most afraid of catching COVID?

To answer these questions, the data used in regression models include:

- **Dependent Variables**: For question 1: change in frequency of total weekly trips to (pre-COVID minus during COVID). For question 2: change in feeling of connectedness to community (pre-COVID minus during COVID). For question 3: fear of catching COVID (the first two models include a scale variable corresponding to the level of fear each individual reports, the third model has a dummy variable of those indicating they are extremely or moderately afraid of catching COVID).
- **Independent Variables**: female, nonwhite, college degree, unemployed, currently employed and working from home, currently employed and commuting, veteran, accessibility issues, unbanked, banked, number of kids in household, married, homeowner, license, car access, age, income level, and fear of COVID.
- **Control (Independent) Variables**: COVID count per 100,000 people in the county during the week of the survey, hospitals and urgent care centers in the county, median household income in the county.

**Table 5**
Anticipated relationship of independent variables with dependent variables.

| Independent Variable | Decrease in Frequency of Trips | Decrease in Connectedness to Community | Fear of COVID |
|---|---|---|---|
| Gender (1 female, 0 male) | + | + | – |
| Race (1 non-white, 0 white) | + | + | + |
| College Degree (1 bachelor's degree or higher, 0 no bachelor's degree) | + | – | – |
| Unemployed (1 unemployed, 0 currently employed at least part time) | + | + | – |
| Currently Employed and Working from Home | – | – | – |
| Currently Employed and Commuting to Work | – | – | + |
| Veteran (1 veteran, 0 non-veteran) | + | + | + |
| Accessibility Issues (1 accessibility/mobility issue, 0 none) | + | + | + |
| Unbanked (1 no checking/ savings account, 0 checking/savings account) | – | + | + |
| Number of Kids (kids in household) | + | + | + |
| Married (1 married, 0 not married) | + | + | + |
| Homeowner (1 own home, 0 rent/other) | + | + | – |
| Valid Driver License (1 license, 0 none) | – | – | – |
| Car Access (1 car access, 0 no car) | – | – | – |
| Age | + | + | + |
| Income Level | + | – | – |
| Fear of COVID | + | + | |
| Number of COVID cases | + | + | + |
| Median Household Income | + | – | – |
| Hospitals and Urgent Care | – | – | – |

The following models provide guidance about the relationships of the dependent variables and independent variables, while controlling for other potentially influential variables related to location and COVID spread at the time of the survey:

**Model 1**

$$\Delta \mathrm{TransitFreq}_i = \beta_0 + \beta_1 W_i + \beta_2 X_i + \mu_i \quad (1)$$

**Model 2**

$$\Delta \mathrm{Connect}_i = \beta_0 + \beta_1 W_i + \beta_2 X_i + \mu_i \quad (2)$$

**Model 3**

$$\mathrm{Fear}_i = \beta_0 + \beta_1 W_i + \beta_2 X_i + \mu_i \quad (3)$$

where:

- β0 = the model intercept
- W = vector for respondent demographics and individual factors, including:
  - Female = A dummy variable for gender
  - Nonwhite = A dummy variable for race
  - College Degree = A dummy variable for bachelor's degree or higher
  - Unemployment = A dummy variable for currently unemployed
  - Employed and Working from Home = A dummy variable for currently employed at least part time and having 0 trips to work
  - Employed and Commuting = A dummy variable for currently employed at least part time and having greater than 0 trips to work
  - Unbanked = A dummy variable for respondent reporting no checking or savings account
  - Banked = A dummy variable for respondent reporting checking or savings account
  - Kids = A ratio variable for number of kids in household
  - Married = A dummy variable for access to marital status
  - Homeowner = A dummy variable for home ownership
  - License = A dummy variable for a valid driver's license
  - Age = Scale variable for age
  - Income (ex 15 K) = Dummy variables for median income in selected range
  - Income Level = Scale variable for income level
  - Fear = A scale variable of how concerned respondent is about catching COVID
- X = vector for local area data, including:
  - COVID = COVID cases per 100,000 people in the week of survey
  - Med HH income = Median household income
  - Hospitals and urgent care = Number of hospitals and urgent care centers in county
    - μ = the error term

Question 1

- ΔTransitFreq = change in frequency of number of trips before/during COVID

Question 2

- ΔConnect = change in feeling of connectedness to community before/during COVID

Question 3

- Fear = A scale variable of how concerned respondent is about catching COVID
- Fear = A dummy variable of whether people are moderately to extremely afraid of catching COVID

*Expected results and descriptive statistics*

Based on existing literature and common sense, our hypotheses are that the following relationships exist, as shown in Table 5:

The descriptive statistics for the dependent and independent variables included in all three models are listed below in Table 6. The numbers in the parentheses indicate the descriptive statistics for the observations excluding those with self-reported bad memories.

*Models and procedures*

After removing personal identifiers from the survey data, we added

**Table 6**
Descriptive statistics for variables.

| Variable | Observations | Mean | Standard deviation | Min | Max |
|---|---|---|---|---|---|
| Dependent variables | | | | | |
| 1. Change in # of trips | 1081 (876) | 4.28 (4.34) | 8.31 (8.43) | −40 (−40) | 72 (72) |
| 2. Change in feeling of connectedness | 1081 (876) | 0.21 (0.22) | 1.11 (1.11) | −4 (-4) | 6 (6) |
| 3a. Fear level | 1081 (876) | 2.21 (2.21) | 1.39 (1.40) | 0 (0) | 4 (4) |
| 3b. Very afraid dummy | 1081 (876) | 0.45 (0.45) | 0.50 (0.52) | 0 (0) | 1 (1) |
| Independent variables | | | | | |
| Female | 1044 (849) | 0.59 (0.58) | 0.49 (0.49) | 0 (0) | 1 (1) |
| Nonwhite | 1063 (863) | 0.42 (0.42) | 0.49 (0.49) | 0 (0) | 1 (1) |
| College degree | 1081 (876) | 0.24 (0.25) | 0.43 (0.43) | 0 (0) | 1 (1) |
| Unemployed | 1081 (876) | 0.36 (0.34) | 0.48 (0.48) | 0 (0) | 1 (1) |
| Employed-working from home | 1081 (876) | 0.03 (0.03) | 0.17 (0.17) | 0 (0) | 1 (1) |
| Employed-commuting | 1081 (876) | 0.50 (0.51) | 0.50 (0.50) | 0 (0) | 1 (1) |
| Currently employed | 1077 (873) | 0.64 (0.65) | 0.48 (0.48) | 0 (0) | 1 (1) |
| Unbanked | 1081 (876) | 0.17 (0.15) | 0.37 (0.36) | 0 (0) | 1 (1) |
| Kids | 1081 (876) | 0.58 (0.57) | 1.16 (1.14) | 0 (0) | 8 (8) |
| Married | 1081 (876) | 0.21 (0.22) | 0.41 (0.42) | 0 (0) | 1 (1) |
| Homeowner | 1080 (876) | 0.22 (0.23) | 0.41 (0.42) | 0 (0) | 1 (1) |
| License | 1081 (876) | 0.43 (0.44) | 0.50 (0.50) | 0 (0) | 1(1) |
| Age | 1081 (876) | 2.32 (2.31) | 1.45 (1.45) | 0 (0) | 5 (5) |
| 15 K | 1081 (876) | 0.16 (0.16) | 0.36 (0.37) | 0 (0) | 1 (1) |
| 25 K | 1081 (876) | 0.12 (0.13) | 0.34 (0.34) | 0 (0) | 1 (1) |
| 35 K | 1081 (876) | 0.09 (0.09) | 0.29 (0.29) | 0 (0) | 0 (1) |
| 45 K | 1081 (876) | 0.13 (0.13) | 0.33 (0.34) | 0 (0) | 1 (1) |
| 55 K | 1081 (876) | 0.03 (0.03) | 0.17 (0.18) | 0 (0) | 1 (1) |
| 65 K | 1081 (876) | 0.03 (0.03) | 0.17 (0.18) | 0 (0) | 1 (1) |
| 75 K | 1081 (876) | 0.01 (0.01) | 0.12 (0.13) | 0 (0) | 1 (1) |
| 85 K | 1081 (876) | 0.01 (0.01) | 0.11 (0.12) | 0 (0) | 1 (1) |
| 95 K | 1081 (876) | 0.01 (0.01) | 0.10 (0.10) | 0 (0) | 1 (1) |
| 120 K | 1081 (876) | 0.06 (0.07) | 0.24 (0.26) | 0 (0) | 1 (1) |
| Income level | 1081 (876) | 3.08 (3.24) | 2.85 (2.95) | 1(1) | 11(11) |
| Extremely concerned | 1081 (876) | 0.24 (0.25) | 0.43 (0.43) | 0 (0) | 1 (1) |
| Moderately concerned | 1081 (876) | 0.21 (0.21) | 0.41 (0.40) | 0 (0) | 1 (1) |
| Somewhat concerned | 1081 (876) | 0.21 (0.22) | 0.41 (0.41) | 0 (0) | 1 (1) |
| Slightly concerned | 1081 (876) | 0.17 (0.17) | 0.38 (0.38) | 0 (0) | 1 (1) |
| Covid per hun thou | 1081 (876) | 447.55 (447.92) | 210.68 (208.20) | 99.8 (99.8) | 711.7 (711.7) |
| Median hh income | 1081 (876) | 59598.13 (59600.3) | 3050.42 (3018.31) | 55,499 (55499) | 64,076 (64076) |
| Hospitals & urgent care | 1081 (876) | 21.52 (21.75) | 10.37 (10.39) | 8 (8) | 34 (34) |

(Descriptive statistics when self-declared bad memory of life pre-covid observations are omitted)

the following variables: county COVID counts per 100,000 people at survey date by county, median household income by county, number of hospitals and urgent care centers in the county, and the differenced pre-and-during COVID values. For the analysis, we excluded observations of those who reported poor memory of their travel activity pre-COVID. This reduced the data set down from 1,081to 876 useful complete observations models. Other models with outliers removed had even fewer observations.

To examine the first question, regarding decrease in frequency of trips, we used both Ordinary Least Squares (OLS) regression model and Maximum Likelihood Estimator (MLE) models. For OLS, two models – one including all observations (N = 842) and one excluding outliers identified through a DF Beta test (N = 558) – were tested for normality, multicollinearity using Klein's Rule and variance inflation factor (VIF) test (the highest VIFs were 3.37 for the first model and 4.17 for the model without outliers), and heteroskedasticity using a Breusch-Pagan-Godfrey test (for both models, we rejected the null hypothesis that there is constant variance (that is, there is heteroskedasticity). To address the heteroskedasticity, we used robust standard errors. Variables such as veteran, accessibility issue, car access, and valid drivers' license were omitted from some of the models after testing for their significance using an incremental F test. Results of each model are shown below in Table 7 and described in the Results section of this paper.

As an alternative model framework, we employed an MLE approach in the context of Poisson regression. Applying OLS regression to count data may lead to incorrect standard errors for significance tests and p-values, although in some instances OLS has been shown to perform better than count models such as Poisson regression when analyzing count data (Sturman, 1999). To address the potential inadequacy of OLS in answering the first question, a Poisson regression model with robust standard errors under a panel framework was fit to the data. The model was specified to include a *during-covid* indicator variable that was interacted with each of the previously described independent variables. This allowed a test for changes in trip counts after the onset of COVID by factors such as gender, race, and unbanked status. The resulting maximum likelihood estimates (MLE) are also shown in Table 7. Thus, the first research question employs four models.

For the second question, who is experiencing the greatest decrease in feelings of connectedness to their community, an OLS regression model with robust standard errors was used, as well as an MLE. Similarly two OLS models – one including (n = 840) and one excluding DF Beta outliers (n = 695) – were used and tested for normality, multicollinearity (VIF), and heteroskedasticity (Breusch-Pagan-Godfrey). Robust standard errors were used to address heteroskedasticity. Results are shown below in Table 8 and described in the Results section.

An ordered logistic regression model with robust standard errors under a panel framework was also used to address the second question. This model also included a *during-Covid* indicator variable that was interacted with each of the regressors, which allowed the study team to test for changes in agreement with the community connectedness statement after the onset of COVID along different respondent characteristics. Responses to this statement were coded from 1 = Strongly Disagree, to 7 = Strongly Agree. The resulting MLE estimates from this analysis are shown below in Table 8.

Finally, for the third question, who is more afraid of catching COVID as it relates to taking public transportation, we also present a regular OLS regression model. These two models were run with (n = 840) and without DF Beta outliers (n = 572). The models were tested for normality, multicollinearity (VIF), and heteroskedasticity (Breusch-Pagan-Godfrey). Because the dependent variable is a scale of the individual's self-reported fear, we also ran an Ordered Logit model as a check, (n = 572). A fourth, Probit model (n = 794) was run to show the probability of individuals with various characteristics to be very afraid of catching COVID on public transportation. COVID fear results are shown in Table 9 and described in the Results section.

### *Regression model results*

*Question 1: Reduction in weekly trips pre-and-during COVID*

Table 7 shows results for the first research question on reduced weekly trip activity. When outliers (found using the DF Beta method) were omitted, the model had 529 degrees of freedom and the adjusted R-Squared of the best model was 0.25, suggesting that this model accounts for 25% of the variance in the decrease in weekly trips. The results show that, all else held constant, we are at least 90% confident in ***all four*** models that being a female, having more kids, and being married resulted in the greatest decreases in the number of trips per week. All else held constant, higher incomes (annual household incomes greater than $90,000) also indicated statistically significant decreases in number of trips from before COVID to during COVID. Conversely, all models show that being unbanked (not having a checking or savings account) suggests that an individual might see an increase in the number of trips taken per week. Fear of COVID does not have a statistically significant relationship to a decrease in number of trips per week; these findings are consistent with Kim et al. (2015)'s findings that socioeconomic status and life circumstances trump fear when it comes to making trips during a pandemic. In terms of local area data, unsurprisingly, counties with higher COVID rates (per 100,000 people) during the week of the survey and with more hospitals and urgent care centers also suggest a greater decrease in the number of trips taken per week. In addition to the models, we also show on the right side of Table 7 the number of times each variable is statistically significant at a 90% level of confidence, as an indicator of robustness[10].

*Question 2: Feelings of connectivity to the community pre-and-during COVID*

Table 8 shows results for the second research question on reported feelings of connectivity to the community before and during COVID. The OLS model that excluded outliers had 676 degrees of freedom, and an R-Squared of 0.06, which suggests that this model accounts for only 6% of the variance of feelings of connectivity before and after COVID. The MLE model showed similar results. Being female, having more kids, and having a $100,000 income or higher indicate a statistically significant decrease in feelings of connectivity to the community during COVID in all four models. Interestingly, the model also shows a relationship between individuals being unbanked (not having a checking/savings account) and experiencing an increase in feelings of connectivity to the community during COVID.

*Question 3: Fear of catching COVID during COVID*

Table 9 shows results for the third set of research questions on who was afraid of contracting COVID. The R-Squared for the OLS model without outliers was 0.23 in the OLS model, suggesting that the model explains 23% of the variance in how much an individual fears catching COVID. The R-Squared for the Ordered Logit model without outliers was 0.09, and results were very consistent with the OLS models. All else held constant, in all four models, being nonwhite, having a college degree, having kids, and having a higher income increases the individual's level of fear of catching COVID (or, in the case of the Probit model, an increase in the predicted probability of being afraid of catching COVID). Being female and being older in age also are related to statistically significant higher fear levels in the two OLS models and Ordered Logit models. Conversely, being employed and having a driver's license decreases the individual's fear level of COVID at a statistical significance of at least 90% in both models. Although not always statistically significant in both models, most of the signs (positive or negative) of the other variables' partial regression coefficients align with our hypothesized outcomes regarding who might be likeliest to have fears of catching COVID on public transportation.

## Conclusions and future research

### *Conclusions*

The results from this study are based on surveys of primarily low-income transit riders from transit agencies serving the cities of Cincinnati, Akron, Canton, and Painesville in Ohio. The research team collected online and a few phone surveys from 1,081 transit riders. The respondents are largely representative of the transit riders in their respective market areas.

Questions focused on destination and trip mode before COVID (February and early March 2020) and during COVID (late 2020), and concerns about contracting the virus. Weekly one-way trips of all types were reduced by 32%. Essential trips like shopping and work trips dropped the least (11–19%), consistent with the findings of Orro et al. (2020). Social visits and worship trips were reduced the most (49–61%). These essential trips are the most popular type of travel undertaken by bus users, so the low drop rate is reassuring for transit companies. Plus, many shopping (especially supermarkets) and work venues were open. On the other hand, social visits such as sporting events and museums and worship venues were largely closed, or constricted, so part of the reduction in trips is due to the destination being unavailable, rather than personal preferences about visiting Grandma, among people that are regular users of public transit.

In terms of travel mode, bus was by far the most common travel mode, and along with personal car use and paratransit dropped the least (about 20% for essential trips), again reassuring for transit agencies dependent upon fare revenue. Walking and ride share for essential travel dropped the most (about 45%). Also, almost half of the respondents were moderately or extremely concerned about catching COVID from other passengers or from touching surfaces/in general, a high percentage that should be of concern to transit agencies. Therefore, when transits clean their rolling stock, they should make sure riders are aware of it. This concern could potentially also provide an opening for touchless fare collection systems like EZfare to gain market share. Unpacking the change in trip types due to COVID is one of our main research contributions.

We also ran a series of regression analyses using demographic characteristics as independent variables, seeking to explain reductions in weekly trips. We found that these factors were most strongly associated with reduced travel: female, married, children at home, incomes over $90,000, and areas with high COVID infection rates. The last finding regarding local COVID infection rates aligns well with Barbieri et al. (2021), who found that one of the largest influences of change in travel behavior was the reported death toll due to COVID per 100,000 inhabitants. However, our results run counter to the findings of Hu and Chen (2021) who found that regions with a smaller decline in transit ridership are more likely to observe a higher rate of COVID cases.

Being employed (including working from home) was associated with stable or increased trips in only our OLS models. Surprisingly, not

[10] We also conducted a set of OLS runs using the outliers-removed sample, with the dependent variable as trips, as opposed to reduction in trips. Separate runs were performed for before COVID and during COVID, with R-squared score between 0.12 and 0.15. The results from those models generally confirmed these findings (in order of magnitude of change, statistically significant changes between the two periods): People with annual incomes over $65,000, married, female, non-whites and respondents with children made fewer trips, as did people where COVID counts in the County were higher. Unbanked people were more likely to make more trips.

**Table 7**
OLS and Poisson regression results – decrease in weekly trips from before to during COVID.

| | OLS with robust SES, excluding bad memory | MLE with robust SES, excluding bad memory | OLS with robust SES, excluding DFBETA outliers and bad memory | MLE with robust SES, excluding DFBETA outliers and bad memory | Number of times significant at least 90% confidence level |
|---|---|---|---|---|---|
| Observations | 842 | 842 | 558 | 558 | |
| F | 3.46*** [813] | 18501*** ($\chi^2$) [63] | 115.71*** [529] | 5327*** ($\chi^2$) [63] | 4 |
| $R^2$ / adjusted $R^2$ | 0.08 / 0.05 | 0.25 (pseudo $R^2$) | 0.29 / 0.25 | 0.25 (pseudo $R^2$) | |
| Intercept | 5.39 (8.99) | 3.26*** (0.80) | 7.20 (4.59) | 2.79*** (0.84) | 2 |
| Demographics | | | | | |
| Female | 1.43*** (0.58) | 0.10** (0.05) | 1.50*** (0.28) | 0.11*** (0.04) | 4 |
| Nonwhite | 0.85 (0.71) | −0.04 (0.06) | 0.76*** (0.31) | −0.001 (0.04) | 1 |
| College degree | 0.80 (0.70) | 0.05 (0.07) | 0.82** (0.40) | 0.08 (0.05) | 1 |
| Unemployed | 0.69 (1.16) | 0.15 (0.12) | 0.63 (0.57) | 0.15 (0.12) | |
| Employed-working from home | −3.15*** (1.20) | −0.23 (0.22) | −1.62** (0.77) | 0.02 (0.21) | 2 |
| Employed-commuting | −0.98 (1.08) | −0.13 (0.11) | −0.90* (0.53) | −0.13 (0.11) | 1 |
| Unbanked | −2.37*** (0.81) | −0.20*** (0.07) | −1.98*** (0.40) | −0.21*** (0.05) | 4 |
| Kids | 0.82** (0.36) | 0.05** (0.02) | 0.50*** (0.15) | 0.05** (0.20) | 4 |
| Married | 1.39* (0.84) | 0.01 (0.07) | 1.61*** (0.44) | 0.05 (0.06) | 2 |
| Homeowner | −0.60 (0.97) | −0.09 (0.09) | −0.99** (0.41) | −0.16** (0.06) | 2 |
| Age | 0.17 (0.22) | 0.04* (0.02) | 0.07 (0.10) | 0.04** (0.02) | 2 |
| 15 K income midpoint | 0.89 (0.77) | 0.10 (0.07) | 1.02** (0.43) | 0.11** (0.05) | 2 |
| 25 K | 0.10 (01.12) | 0.05 (0.09) | 0.57 (0.46) | 0.08 (0.06) | |
| 35 K | 0.46 (1.71) | 0.13 (0.10) | −0.59 (0.69) | 0.13** (0.06) | 1 |
| 45 K | 0.61 (1.48) | 0.12 (0.15) | 1.56** (0.64) | 0.27*** (0.09) | 2 |
| 55 K | 1.00 (1.30) | 0.20* (0.11) | 1.27* (0.71) | 0.24** (0.10) | 3 |
| 65 K | 1.57 (1.07) | 0.37** (0.15) | 2.91*** (0.89) | 0.49*** (0.16) | 3 |
| 75 K | 0.75 (2.27) | 0.18 (0.18) | 4.29*** (1.19) | 0.37* (0.19) | 2 |
| 85 K | 3.87* (2.19) | 0.48*** (0.17) | 4.58*** (0.64) | 0.12 (0.13) | 3 |
| 95 K | 4.64** (2.39) | 0.65*** (0.20) | 7.11*** (0.83) | 1.31*** (0.16) | 4 |
| 120 K | 2.55* (1.56) | 0.23* (0.13) | 2.62*** (0.69) | 0.29*** (0.10) | 4 |
| Fear of COVID | | | | | |
| Extremely concerned | 1.40 (1.02) | 0.12 (0.08) | 0.56 (0.46) | 0.06 (0.06) | |
| Moderately concerned | −0.07 (0.97) | 0.06 (0.08) | −0.23 (0.44) | −0.01 (0.06) | |
| Somewhat concerned | 1.04 (0.97) | 0.14* (0.08) | 0.62 (0.45) | 0.10* (0.06) | 2 |
| Slightly concerned | 0.75 (1.00) | 0.09 (0.08) | −0.002 (0.47) | 0.02 (0.06) | |
| Local area data | | | | | |
| COVID per hun thou | 0.004* (0.002) | 0.0004** (0.0002) | 0.005*** (0.001) | 0.0004*** (0.0002) | 4 |
| Median hh income | −0.0001 (0.0002) | −2.0e-05 (1.4e-05) | −0.0002** (0.0001) | −1.5e-05 (1.1e-05) | 1 |
| Hospitals and urgent care | 0.07** (0.03) | 0.008*** (0.003) | 0.08*** (0.02) | 0.009** (0.002) | 4 |

* p value less than 0.10, ** p value less than 0.05, *** p value less than 0.01
(standard error) [degrees of freedom]
self-declared bad memory of life pre-COVID omitted in both runs

having a bank account was also associated with stable or increased trips. This supports the notion that unbanked people are more transit-dependent and have fewer travel options, unlike their more affluent co-riders who can opt for delivery services such as Uber Eats or Instacart.

We also ran models on self-reported feeling of connectivity to the community. Females, those with children, and those earning over $100,000 per year were associated with were feeling less connected. Unbanked people did not generally report experiencing a loss of connectivity, probably because their travel patterns were relatively undisrupted.

Our final set of runs addressed fear of catching COVID. The respondents who were more likely to have an increased fear of catching COVID were: nonwhite, having kids, having a college degree, and having a higher income. Conversely, being employed or having a driver's license decreased the chances that the individual was afraid of COVID. This makes sense because non-whites have a greater chance of a negative outcome stemming from COVID (CDC, 2021). Again, the potential benefits of a touchless payment system may appeal to a large percentage of riders, both in general, and for those with concern about touching surfaces.

To summarize, reduced travel behavior in the middle of the COVID epidemic is largely borne disproportionately by females, married people, having children at home, having incomes over $80,000, and in areas with high COVID infection rates. Unbanked people overall did not report trip reductions or increased feelings of being disconnected to the community. Some other findings: holding all else constant, veteran or disability status, number of vehicles, home ownership, and access to a car at home did not appear to be a significant factor in any of our models. Also, fear of catching COVID did not noticeably impact on people's travel behavior.

The regression results that associate various demographics with the change in trips, feelings of connectivity, and fear of contracting COVID are also main research contributions.

Our study has some limitations. Although our models used appropriate procedures and duplicated different forms of multivariate analysis to test for robustness of findings, and also had corroborating descriptive statistics, we had relatively low R-squared statistics in some models. Our research is strictly based on a stated preferences survey and is not corroborated with actual behavior.

### Future research

Although public transit ridership has been recovering from the nadir of April and May 2020, the recovery is still ongoing: three of our four

**Table 8**
OLS and ordered logit regression results – decrease in feelings of connectedness to community.

| | OLS with robust SES, excluding bad memory | MLE with robust SES, excluding bad memory | OLS with robust SES, excluding DFBETA outliers and bad memory | MLE with robust SES, excluding DFBETA outliers and bad memory | Number of times significant at least 90% confidence level |
|---|---|---|---|---|---|
| Observations | 840 | 840 | 695 | 695 | |
| F | 2.29*** [821] | 111.56*** ($\chi^2$) [37] | 3.43*** [676] | 105.82*** ($\chi^2$) [37] | 4 |
| R2 / adjusted $R^2$ | 0.05 / 0.03 | 0.07 (pseudo $R^2$) | 0.06 / 0.04 | 0.07 (pseudo $R^2$) | |
| Intercept | 1.91 (1.33) | | 1.60*** (0.61) | | 1 |
| Demographics | | | | | |
| Change in number of trips | 0.01 (0.01) | 0.01 (0.01) | 0.004* (0.002) | 0.004 (0.015) | 1 |
| Female | 0.18** (0.08) | 0.50** (0.22) | 0.07* (0.04) | 0.36** (0.22) | 4 |
| Nonwhite | 0.07 (0.08) | 0.22 (0.23) | 0.004 (0.04) | 0.05 (0.23) | |
| Currently employed | −0.08 (0.09) | −0.30 (0.28) | −0.07 (0.05) | −0.11 (0.27) | |
| Unbanked | −0.33*** (0.10) | −0.91*** (0.31) | −0.19*** (0.05) | −0.79*** (0.29) | 4 |
| Kids | 0.08* (0.04) | 0.23* (0.13) | 0.03 (0.02) | 0.21* (0.12) | 3 |
| 15 K income midpoint | 0.07 (0.12) | 0.20 (0.36) | 0.05 (0.07) | 0.17 (0.33) | |
| 25 K | 0.21 (0.13) | 0.38 (0.39) | 0.16** (0.07) | 0.65* (0.36) | 2 |
| 35 K | −0.39 (0.28) | −0.38 (0.38) | −0.20 (0.13) | −0.27 (0.36) | |
| 45 K | 0.29 (0.27) | 0.46 (0.65) | 0.22* (0.12) | 0.18 (0.62) | 1 |
| 55 K | −0.04 (0.22) | −0.04 (0.61) | 0.20 (0.14) | −0.11 (0.65) | |
| 65 K | −0.02 (0.24) | −0.02 (0.65) | 0.14 (0.16) | 0.05 (0.67) | |
| 75 K | 0.07 (0.14) | 0.30 (0.53) | 0.16 (0.12) | 0.50 (0.55) | |
| 85 K | 0.31* (0.18) | 0.97 (0.66) | 0.29** (0.14) | 1.41* (0.74) | 3 |
| 95 K | 0.31 (0.27) | 0.74 (0.89) | 0.21 (0.19) | 1.14 (1.00) | |
| 120 K | 0.34*** (0.13) | 0.94** (0.43) | 0.28*** (0.08) | 1.25*** (0.41) | 4 |
| Local area data | | | | | |
| COVID per hun thou | 0.0004 (0.0003) | 0.001 (0.009) | 0.0003* (0.0002) | 0.001 (0.001) | 1 |
| Median hh income | −0.00003 (0.00002) | −0.00008 (0.00007) | −0.0003*** (0.0001) | −0.0001** (0.00006) | 2 |

* p value less than 0.10, ** p value less than 0.05, *** p value less than 0.01
(standard error) [Degrees of freedom]
self-declared bad memory of life pre-COVID omitted in both runs

**Table 9**
OLS, ordered logit, and Probit regression results – fear of catching COVID.

| | Fear level (0–4) scale | | Fear level (0–4) Scale | More afraid dummy | |
|---|---|---|---|---|---|
| | OLS, excluding bad memory | OLS, excluding DFBeta outliers and bad memory | Ordered Logit, excluding DFBeta outliers from OLS model and bad memory | Probit. excluding DFBeta outliers from OLS model and bad memory | Number of times significant at least 90% confidence level |
| Observations | 840 | 572 | 572 | 794 | |
| F Statistic/LR chi2 | 5.82*** | 16.65*** | 155.01*** | 50.40*** | 4 |
| Adj-$R^2$ or pseudo $R^2$ | 0.07 | 0.23 | 0.09 | 0.05 | |
| Intercept | 1.26*** (0.21) | 0.99*** (0.20) | | −0.83*** (0.21) | 3 |
| Demographics | | | | | |
| Total trips during COVID | −0.01 (0.01) | −0.003 (0.01) | −0.01 (0.01) | −0.003 (0.01) | |
| Female | 0.20** (0.09) | 0.32*** (0.08) | 0.61*** (0.16) | 0.11 (0.09) | 3 |
| Nonwhite | 0.41*** (0.10) | 0.73*** (0.09) | 1.39*** (0.18) | 0.42*** (0.10) | 4 |
| College degree | 0.22* (0.13) | 0.30*** (0.12) | 0.57*** (0.22) | 0.21* (0.12) | 4 |
| Currently employed | −0.25** (0.11) | −0.40*** (0.10) | −0.78*** (0.19) | −0.34*** (0.11) | 4 |
| Kids | 0.12*** (0.04) | 0.12*** (0.04) | 0.25*** (0.08) | 0.09** (0.04) | 4 |
| License | −0.21** (0.10) | −0.41*** (0.09) | −0.79*** (0.18) | −0.17* (0.10) | 4 |
| Age | 0.08** (0.03) | 0.12***(0.03) | 0.24*** (0.06) | 0.04 (0.03) | 3 |
| Income level | 0.04* (0.20) | 0.06*** (0.02) | 0.12*** (0.03) | 0.04** (0.02) | 4 |
| $A = \pi r^2$ data change to Local Area Data , no equation here! | | | | | |
| COVID per hun thou | 0.001*** (0.0002) | 0.001*** (0.0002) | 0.002*** (0.0004) | 0.001*** (0.0002) | 4 |
| Hospitals and urgent care | 0.01** (0.01) | 0.01** (0.005) | 0.02** (0.01) | 0.01 (0.005) | 3 |

* p value less than 0.10, ** p value less than 0.05, *** p value less than 0.01
(standard error)
Self-declared bad memory of life pre-COVID omitted in both runs

transit agencies ridership levels 23–47% lower than the previous year. Some types of trips such as school, medical, and those to social and worship destinations were greatly reduced during the pandemic, and when and under what conditions they will recover to their former capacities is of yet unknown. Once vaccination has become widespread and the virus is under control we should see those trips recover—but how quickly and to what extent? In June 2021, the Governor of Ohio abolished all public COVID related restrictions such as wearing a mask and social distancing, although the FTA still requires that masks be worn on public transit through September 2021. Thus, future iterations of this panel study should reveal the degree to which transit behavior bounces back to pre-COVID levels. Technology may intervene: recent trends in tele-medicine and new comfort with working from home could mean that these trips may not fully recover to pre-pandemic levels. There is also anecdotal information that more people are moving out of the large, expensive cities to suburban and smaller metro areas, and that dense urban living may fall out of fashion, for a time. Obviously, de-densification of urban transit agencies' service areas would work against more efficient operations. Also, it appears that new types of employers like Gojo (maker of Purell) and VXI (in-bound call center) are thriving and adding employees. Since working from home provides middle-to-upper income people with more work options, there could be an increased gap in access to employment between those that are truly dependent on public transit and those that have other options. The challenge for transit is to be able to flexibly satisfy these changing trends and meet the new trip needs.

Some implications for transit practitioners and system operators: As we start the recovery, ridership is starting to come back. However, inconsistent guidance between the state and federal regulators are starting confusion (for example, about wearing masks). Hopefully, the recovery trend will continue as the COVID vaccines are distributed, and any future variants can be mitigated with COVID booster shots.

In the future, it will be necessary to understand the possible recovery of transit ridership and the general economy. It will also be critical to understand if the unbanked and the economically disadvantaged are able to recover both economic well-being and their sense of community connectedness. Lastly, it will be interesting to see if COVID accelerates the transition to touchless fare media like EZFare and the continued decline of the use of cash.

As a result of COVID, transit systems will need to modify services, routes, and headways. Additionally, transit systems will need use greater levels of technology to connect first-and-last mile destinations. With the advent of rideshare/hail companies, people already have been moving to a more individualized mobility. These trends were already occurring and COVID accelerated the trend. Transit systems will have to embrace these new trends in order to meet the needs of their communities.

Given these trends, future research should monitor how the various types of destinations and trip modes return to their pre-COVID levels. Another fruitful area could examine the effectiveness of various technological innovations, including touchless payment systems and related apps, on travel outcomes, and quality of life (access to work, shopping, medical care, etc.) with attention paid to the most vulnerable customers: low-income and unbanked transit riders. This research shows that married women with children were the most likely to stop using transit. Systems in the future will have to conduct outreach and education to get these riders back.

## CRediT authorship contribution statement

**Robert A. Simons:** Conceptualization, Validation, Methodology, Formal analysis, Supervision, Project administration, Funding acquisition. **Mark Henning:** Methodology, Formal analysis, Investigation, Data curation. **Abigail Poeske:** Methodology, Validation, Formal analysis, Data curation, Visualization. **Malcolm Trier:** Investigation, Visualization. **Kirt Conrad:** Validation.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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