

UC Office of the President

ITS reports

Title

Rail Transit Ridership Changes and COVID-19: Lessons from Station-Area Characteristics

Permalink

<https://escholarship.org/uc/item/07b5s42c>

Authors

Li, Meiqing

Rodríguez, Daniel A., PhD

Pike, Susie, PhD

et al.

Publication Date

2024-09-01

DOI

10.7922/G2G44NNX

Rail Transit Ridership Changes and COVID-19: Lessons from Station-Area Characteristics

Meiqing Li, Ph.D. Candidate, Department of City and Regional
Planning, University of California, Berkeley

Daniel A. Rodríguez, Ph.D., Chancellors Professor, Department of
City and Regional Planning, University of California, Berkeley

Susie Pike, Ph.D., Professional Researcher, Institute of
Transportation Studies, University of California, Davis

Michael McNally, Ph.D., Professor, Department of Civil and
Environmental Engineering, University of California, Irvine

September 2024



Technical Report Documentation Page

1. Report No. UC-ITS-RIMI-4D		2. Government Accession No. N/A		3. Recipient's Catalog No. N/A	
4. Title and Subtitle Rail Transit Ridership Changes and COVID-19: Lessons from Station-Area Characteristics				5. Report Date September 2024	
7. Author(s) Meiqing Li, PhD Candidate, https://orcid.org/0000-0001-8860-1174 ; Daniel A. Rodríguez, Ph.D., https://orcid.org/0000-0001-6550-5518 ; Susie Pike, Ph.D. https://orcid.org/0000-0001-6558-3479 ; Michael McNally, Ph.D.				6. Performing Organization Code ITS Berkeley, ITS-Davis, ITS-Irvine	
9. Performing Organization Name and Address Institute of Transportation Studies, Berkeley 109 McLaughlin Hall, MC1720, Berkeley, CA 94720-1720 Institute of Transportation Studies, Davis 1605 Tilia Street, Davis, CA 95616 Institute of Transportation Studies, Irvine 4000 Anteater Instruction and Research Building, Irvine, CA 92697				8. Performing Organization Report No. N/A	
12. Sponsoring Agency Name and Address The University of California Institute of Transportation Studies www.ucits.org				10. Work Unit No. N/A	
15. Supplementary Notes DOI: 10.7922/G2G44NNX				11. Contract or Grant No. UC-ITS-RIMI-4D	
16. Abstract The COVID-19 pandemic has had a significant impact on public transit ridership in the United States, especially for rail transit. Land use, development density, and the pedestrian environment are strongly associated with station-level transit ridership. This study examines how these characteristics affect transit ridership pre- and post-COVID and how they differ across station types based on longitudinal data for 242 rail stations belonging to Bay Area Rapid Transit, San Diego Metropolitan Transit System, Sacramento Regional Transit, and LA Metro between 2019 and 2021. We found overall a 72% decrease in station-level ridership, but changes were not uniform. Station areas with a higher number of low-income workers and more retail or entertainment jobs tend to have lower ridership declines, while areas with a large number of high-income workers, high-wage jobs, and higher job accessibility by transit had more ridership losses. When comparing station area ridership and activity changes based on mobile phone user data, ridership declined more drastically than activity across all four rail systems, which implies that rail transit riders switched to other modes of transportation when accessing the station areas. Given these findings, it is likely that rail transit services oriented toward commute travel, especially core station areas with jobs for higher income workers, will continue to have an uneven recovery, posing critical implications for transit resilience planning and equity in the post-pandemic era. Considering sources of funding other than passenger fares to sustain rail transit, strategizing to reinvent and reinforce downtowns as destinations, and shifting rail transit services to appeal to non-commute travel can be promising strategies to support rail transit.				13. Type of Report and Period Covered Final Report (February 2022–June 2023)	
17. Key Words Rail transit, ridership, rail transit stations, travel behavior, mode choice, demographics, financing				14. Sponsoring Agency Code UC ITS	
19. Security Classification (of this report) Unclassified		20. Security Classification (of this page) Unclassified		18. Distribution Statement No restrictions.	
				21. No. of Pages 36	
				22. Price N/A	

Form Dot F 1700.7 (8-72)

Reproduction of completed page authorized

Rail Transit Ridership Changes and COVID-19: Lessons from Station-Area Characteristics

Meiqing Li, Ph.D. Candidate, Department of City and Regional Planning, University of California, Berkeley

Daniel A. Rodríguez, Ph.D., Chancellors Professor, Department of City and Regional Planning, University of California, Berkeley

Susie Pike, Ph.D., Professional Researcher, Institute of Transportation Studies, University of California, Davis

Michael McNally, Ph.D., Professor, Department of Civil and Environmental Engineering, University of California, Irvine

September 2024

Table

of

Contents

The UC Institute of Transportation Studies

The University of California Institute of Transportation Studies (UC ITS) is a network of faculty, research and administrative staff, and students dedicated to advancing the state of the art in transportation engineering, planning, and policy for the people of California. Established by the Legislature in 1947, ITS has branches at UC Berkeley, UC Davis, UC Irvine, and UCLA.

The California Resilient and Innovative Mobility Initiative

The California Resilient and Innovative Mobility Initiative (RIMI) serves as a living laboratory—bringing together university experts from across the four UC ITS campuses, policymakers, public agencies, industry stakeholders, and community leaders—to inform the state transportation system’s immediate COVID-19 response and recovery needs while establishing a long-term vision and pathway for directing innovative mobility to develop sustainable and resilient transportation in California. RIMI is organized around three core research pillars: Carbon Neutral Transportation, Emerging Transportation Technology, and Public Transit and Shared Mobility. Equity and high-road jobs serve as cross-cutting themes that are integrated across the three pillars.

Acknowledgments

This study was made possible through funding received by the Resilient and Innovative Mobility Initiative from the State of California through a one-time General Fund allocation included in the 2021 State Budget Act. The authors would like to thank the State of California for its support of university-based research and especially for the funding received for this project. The authors would also like to thank Matthew Hui for his excellent research assistance.

Disclaimer

The contents of this report reflect the views of the author(s), who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the State of California in the interest of information exchange. The State of California assumes no liability for the contents or use thereof. Nor does the content necessarily reflect the official views or policies of the State of California. This report does not constitute a standard, specification, or regulation.

Table of Contents

Executive Summary	1
Introduction	3
Previous Studies on Post-COVID Transit Recovery	3
Station-Area Characteristics and Transit Ridership	4
Research Questions	5
Methodology	6
Data	6
Statistical Analyses	7
Findings	9
Rail Transit Ridership Changes in COVID-19	9
Associations between Rail Transit Ridership Changes and Station-Area Characteristics	12
Station-Area Activity Changes	16
Conclusions	23
References	25

List of Tables

Table 1. Number of Stations for Each Selected Rail Transit Agency in California 6

Table 2. Summary Statistics of Dependent and Independent Variables (n = 242).....12

Table 3. Linear Regression Associations between Station-Area Characteristics and Percent Change in Average Weekday Ridership (Errors Clustered by Line).....13

Table 4. Mean Values of Station-Area Characteristics and Percent Change in Ridership and Number of Visits per Capita by Cluster (n = 180)..... 20

List of Figures

Figure 1. Pre-COVID and Post-COVID Ridership of Rail Transit Agencies in California for 242 Stations (left: February 2019; right: February 2021)..... 9

Figure 2. Percent Change in Station-Level Average Weekday Ridership of 242 Rail Transit Agencies in California10

Figure 3. Percent Change of Average Weekday Ridership by Station between February 2019 and 2021 (n=242)11

Figure 4. Model Residuals for Each Station by Transit System 15

Figure 5. Percent Change in Station-Area Visits (n = 176; Four Outlying Observations Excluded) 16

Figure 6. Station Area Types by System Based on Station-Area Characteristics19

Figure 7. Relationship between Percent Change in Average Weekday Ridership and Number of per Capita Station-Area Visits.....22

Executive

Summary

Executive Summary

Emerging evidence suggests that the post-COVID recovery of transit ridership has been uneven. Some bus systems have reached or surpassed their pre-COVID ridership levels, while others continue to struggle. For rail transit, the vast majority of systems still under their pre-COVID ridership levels, but significant variation remains. For example, stations serving the central business district (CBD) exhibit larger passenger losses than suburban stations with mixed income residents and land uses, although these effects appear to differ by transit system and metropolitan area. In this study, we investigate these questions:

- What are the station-level ridership changes in four of California’s largest rail transit agencies and what accounts for differences in these changes?
- Are the ridership changes related to overall activity decreases in station areas, or are the changes specific to rail transit?
- How can the results inform strategies for the recovery of rail transit?

We examined ridership changes between 2019 and 2021 for 242 stations belonging to Bay Area Rapid Transit (BART), San Diego Metropolitan Transit System (MTS), Sacramento Regional Transit (SACRT), and LA Metro. We then associated these changes with the built environment, socio-demographics, and the location of the stations within the network of stops for each system. We also compared the ridership changes to overall activity changes in the station area (e.g., decreases in trip making, regardless of travel mode, ending in the station area).

The pandemic had a significant impact on all four rail systems. The stations had a 72 percent average decrease in station-level ridership between 2019 and 2021—BART had the greatest decrease (87 percent), and MTS had the lowest (47 percent). Most ridership decreases were specific to individual stations, for example, those located in downtowns or at terminals, or appeared related to specific lines, especially for LA Metro and MTS. We found that station areas with a higher number of low-income workers and more retail or entertainment jobs had lower ridership declines, while areas with a higher number of high-income workers, more high-wage jobs, and higher job accessibility by transit had more ridership losses. When comparing ridership and overall activity changes from mobile phone user data, we found that ridership declined more drastically than activity across all four rail systems, which implies that either some rail transit riders switched to other modes of transportation when accessing the station areas or activity from non-transit users increased.

These results suggest that rail transit services oriented toward serving the work commute, especially core station areas with jobs for higher income workers, are likely to continue having an uneven recovery. The changes documented, and the station-area environmental characteristics associated with those changes, reinforce the pre-pandemic pattern of California transit riders being fewer and poorer over time. Considering sources of funding other than passenger fares to sustain rail transit, strategizing to reinvent and reinforce downtowns as destinations, and shifting rail transit services to appeal to non-commute travel can be promising strategies to support rail transit.

Contents

Introduction

The COVID-19 pandemic has had a significant impact on public transit ridership in the United States. Ridership has declined by as much as 80 percent in some cities and is still recovering (Bureau of Transportation Statistics 2021). According to the American Public Transportation Association, 76 percent of agencies responding to a survey conducted in March 2020 indicated that they have experienced a ridership decrease. For example, New York City’s MTA lost 667 million riders in 2020, a 63 percent drop from the previous year. The Washington Metropolitan Area Transit Authority (WMATA) had a 79 percent drop from 2019’s 248 million riders (Bureau of Transportation Statistics 2021). The trend continued in the following months amid COVID-19. Ridership gradually recovered in 2022 post pandemic, although it was still below the pre-pandemic levels (Doyle 2023). A number of factors contributed to this decline, including public health concerns about the spread of COVID-19 on public transit, increased work-from-home options, and transit service cuts during the pandemic. Although ridership has continued to improve for some agencies, overall ridership levels remain lower than before the pandemic. In California, with some exceptions, transit ridership had been declining even before the pandemic, with the San Francisco Bay Area and the Greater Los Angeles Area losing between 10 and 25 percent of transit boardings per capita between 2008 and 2018 (Taylor, et al. 2020). The pandemic added a significant drop in ridership and related challenges. For example, Bay Area Rapid Transit (BART) lost more than 70 percent of the ridership between 2019 and 2020 (Urban Institute 2021).

The decrease in ridership has negative consequences to transit revenue that eventually could translate into a vicious cycle where reduced transit services result in additional ridership decline. Decreases in service impacts access to jobs, education, and other essential services, especially for the transit-dependent population. Moreover, failing to attract ridership undermines the achievement of long-term sustainable transportation goals.

Beyond agency-wide decreases in ridership, there is significant variation in the changes within each transit system. Anecdotal evidence and media reports suggest that changes in ridership can vary dramatically by stop and geography. Stops that served a higher percentage of commuters were more likely to see ridership decrease because of shelter-in-place and telework. Ridership decline was also more severe in urban areas where travel is more reliant on public transit. It is likely that the type of users, the built environment and land use characteristics, and the socio-economic characteristics of riders can help explain differences in ridership changes by stop.

Previous Studies on Post-COVID Transit Recovery

Numerous studies have researched the impact of COVID-19 on travel behavior and transit ridership in the midst of the early pandemic. Studies focusing on the United States have documented consistent findings of a greater reduction in the number of trips made by transit relative to other modes (Lee and Eom 2023; Parker, et al. 2021). Some studies analyzed the socio-demographic disparity of ridership change in station-area

communities during COVID-19. One study by the Urban Institute (2021), which examined four transit systems in the United States (WMATA, New York City Subway, Chicago 'L', and Bay Area Rapid Transit), found that transit ridership fell most dramatically in job centers but less in communities with more Black residents, lower-income populations, and a higher number of working-class jobs. Such disparities have critical equity implications, because it is the residents in these communities who have to use transit to get to and from jobs.

Despite the abundance of empirical studies on COVID's impact, studies have yet to examine the aftermath of the pandemic on ridership, nor has existing work explored the effect of governmental planning and policy response in supporting ridership recovery (Kamargianni, et al. 2022). Transportation, land use, and the built environment, in addition to service provision and fare policies, need to be coordinated to address the socio-demographic disparity that is associated with uneven ridership changes. Bringing back transit partly relies on bringing back activities to urban areas (Kim 2021). So far, few studies have investigated the connection between ridership recovery and station-area neighborhood characteristics, including the built environment, network configuration, and overall mobility changes.

Station-Area Characteristics and Transit Ridership

The land use composition and development intensity of a station area is a determinant of stop use. Station areas with office and commercial uses and a mixture of uses tend to see higher demand than station areas focused solely on residential uses (Cervero and Murakami 2008; Vergel-Tovar and Rodriguez 2018). Development density is also highly associated with transit demand (Ewing and Cervero 2010). Studies around the world have found similar patterns that higher density station areas drive more station-level ridership (Andersson, et al. 2021; Guzman and Gomez Cardona 2021). Other studies found that adjusted parking supply and pricing can support transit ridership (Willson 2005).

In addition, the location of stations relative to one another is an important transit network characteristic that explains station use. Stations located downtown, in transfer locations, and more centrally are likely to have higher ridership. For example, Vergel-Tovar and Rodriguez (2018) examined bus rapid transit station demand in eight Latin American cities and found that transfer stations with public and institutional uses, a high mixture of land uses, and located away from the CBD had 316.46 percent more ridership compared with suburban industrial stations. Similarly, examining all mass transit stops in Seoul, Rodríguez and Kang (2020) found that centrality played a key role in explaining passenger demand. These findings show that a station node's relative location affects ridership.

The urban design of a station area is another characteristic that determines transit ridership. For example, if local access to a transit stop is thwarted by wide streets with fast-moving vehicles, transit ridership suffers. Similarly, the presence of crosswalks in station areas is expected to increase transit ridership (Li, et al. 2022). Other research has shown how improving the pedestrian environment is associated with higher mass transit demand (Abdel-Salam 2014; Rodríguez, et al. 2009; Ryan and Frank 2009).

In sum, empirical evidence suggests that land use, development density, and the pedestrian environment are strongly associated with station-level transit ridership. In the context of the pandemic and its impacts on transit demand, it is likely that the importance of these factors in affecting ridership will carry over to the post-pandemic world but differently. This project examines how the ridership changes differ across stations with various built environments, socio-demographic characteristics, and network configuration based on longitudinal data for stations belonging to BART, San Diego MTS, SACRT, and LA Metro. Findings from this project will have critical implications for transit resilience planning and equity in the post-pandemic era.

Research Questions

This project centers around three overarching research questions to investigate the relationship between ridership changes during COVID-19 and station characteristics.

1. *What are the station-level ridership changes between 2019 and 2021?*

These two years marked the time points when ridership was at the pre-COVID and post-COVID levels. Comparing station-level ridership before, during, and after the pandemic provides a comprehensive view of how the impact differs across geography and systems.

2. *Which station-level characteristics, such as population density, job composition (office, retail, institutional), neighborhood economics (low vs. other income), or position within the public transit network (central transfer node vs. peripheral node) are associated with a stronger ridership recovery?*

In addition to the socio-demographic factors, land use, network configuration, and other built environment characteristics can affect the speed of both ridership drop and ridership recovery. This question tests the hypotheses to determine the key factors that contribute to transit ridership change and to identify targeted strategies for ridership recovery.

3. *To what extent are the decreases specific to rail transit, or do they reflect overall activity changes regardless of travel mode? Are the changes in ridership similar to overall visits to station areas?*

This question assesses whether the drop in ridership is due to overall activity changes regardless of travel mode or whether there is a shift from rail transit to other modes, such as alternative bus services, driving, walking, or biking.

Methodology

The following sections introduce the data and methods used for answering the three research questions. For the first question, we compare station-level ridership data for the four rail transit systems. For the second question we examine associations between ridership changes and station-level characteristics. For the third question, we relied on a location-based service (LBS) dataset managed by Embee (now acquired by similarweb, <https://www.similarweb.com>), a private marketing research firm, which recorded all destinations of activities in a sample of mobile phone users across California since 2020.

Data

Station Ridership

We collected station-level average weekday ridership in 2019 (pre-COVID) and in 2021 (post-COVID) from four California transit agencies (BART, LA Metro, San Diego MTS, and SACRT) that operate a total of 246 rail stations. We excluded two new stations that were not open in 2019, and two stations that closed between the two years, resulting in a sample of 242 stations. For BART and SACRT, we used February average weekday ridership for 2019 and 2021. Because monthly ridership data was not available for LA Metro and MTS, we used annual average weekday ridership for LA Metro, and spring 2019 and 2021 average weekday ridership for MTS. **Table 1** summarizes the number of stations belonging to each agency.

Table 1. Number of Stations for Each Selected Rail Transit Agency in California

Agency	BART	LA Metro	MTS	SACRT	Total
Number of Stations	47	91	52	52	242

Built Environment Characteristics

We compiled socio-demographic and built environment variables for all 242 stations using the Environmental Protection Agency’s Smart Location Database (SLD 2020). Measures included jobs or population density, percent of jobs by industry (e.g., retail, industry, entertainment, health care), road network density, and resident characteristics (percent of residents by income and car ownership). In addition, we identified the stations within that fell within the top quartile of CalEnviroScreen 4.0 scores.¹ Because the unit of analysis for the SLD is census block group, we aggregated each variable to a weighted average by overlapping the area of each census block group with the half-mile station radius.

¹ https://experience.arcgis.com/experience/11d2f52282a54cee9cac7428e6184203/page/CalEnviroScreen-4_0/

Transit Station Locations and Service Characteristics

Because transit service changed over time due to the pandemic, we measured service levels at each station. We used the General Transit Feed Specification data to obtain average hourly train departures scheduled from each station during 2019 and 2021. The same data was used to derive the betweenness centrality of each transit station relative to the transit network (Brandes 2008; Freeman 1977) by constructing directional networks using the Python package NetworkX. This measure describes the degree to which a node is in the shortest path between every other pair of nodes, denoting the node's importance in connecting trips across stations in the transit network.

Activity Around Station Areas

We processed LBS data provided by Embee for every month between January 2020 and December 2022 for over 5,000 California residents. This sample is dynamic because participants can opt in and out of the survey while enrolled. The original data contains trip information, including the start and end locations and time, for each individual mobile phone user within the sample during the period determined by Embee. Our February 2020 sample consists of 5,330 California residents, while the February 2021 sample contains 4,583 people whose home location was in California.

To make the data comparable across the years and consistent with ridership data, we selected data for the entire month of February in 2020 and 2021 and counted the total number of visits to the half-mile station area buffers during each month. The final dataset contains the number of visits regardless of travel mode for those two years, representing pre-COVID and post-COVID station-area activity. Because the sample size changed over time, we normalized the number of trips to the station area by sample size to get the average number of visits per capita in each period.

Statistical Analyses

Ridership Changes over Time and Predictors

To answer our first research question, we used descriptive statistics and boxplots by agency to summarize ridership and changes over time. For our second research question examining the predictors of ridership change, we estimated an ordinary least squares linear regression model to determine associations between rail transit ridership changes and station area characteristics. We identified a list of independent variables measuring characteristics that potentially can affect changes in ridership, including socio-economic and built environment characteristics of station area neighborhoods. Specifically, we considered job and population density, diversity of land uses (composition) as well as urban design characteristics, such as road network density and pedestrian accessibility in each station area. Because these characteristics are likely to vary simultaneously (for example, where there is high population density, there might be a higher mixture of land uses), we used variance inflation factors (VIF) to determine multicollinearity among variables and eliminated variables where $VIF > 10$. We estimated the model in R using the `lm()` function.

Station-level regression models use ridership change as the dependent variable and other variables as independent variables. The model specification is as follows, with no subscripts shown for simplicity:

$$\Delta Ridership = f(BE, Station\ node\ location)$$

where

- $\Delta Ridership$ is the change in average weekday station ridership between 2019 and 2021 for each station
- BE is the station-area built environment characteristics vector
- $Station\ node\ location$ represents the network betweenness centrality of the station node

Coefficients estimated for the built environment characteristics and station node location summarize associations between each variable and how ridership changed before and after the pandemic. We plotted the residuals by station to identify potential patterns of spatial correlation and adjusted for it when necessary.

Are Ridership Changes the Result of Decreases in Overall Activity?

Because the sample size for passive mobility data in each station area is relatively small, we aggregated stations into groups or station types based on their similarity for built environment variables. To do so, we applied a k-means clustering algorithm (Macqueen 1967) to group similar stations into clusters. We used the NbClust function in R and a combination of the majority rule and prior experience to identify the optimal number of station types separately for each transit system. We then calculated the total number of visits per capita within a half-mile radius of each station type in February 2020 and 2021, respectively. We then compared changes in ridership with changes in total number of visits per capita across station type for each transit system.

Limitations

We did not control for changes in alternative transit services, such as buses. We did measure train service, but as discussed below, its inclusion in the model raises questions about endogeneity. We partially mitigated this concern by using mobile phone data to estimate overall activity changes in station areas, which accounts for trips by all modes. Secondly, we examined changes in ridership between 2019 and 2021 with built environment data from 2018. With COVID, the environment changed rapidly because stores and offices were closed. We only measured those closures indirectly through the prevailing land uses in 2018. Whether those uses were active and open for business is unclear. Should more recent or even longitudinal data become available, they can more accurately represent the built environment surrounding transit stations as well as its change over time. This includes, for example, street closures and other pandemic-related adjustments to the use of space.

Another limitation is that our sample size of mobile phone data is relatively small, especially when we filter only trips to the half-mile buffer of transit stations. With a larger sample of passive data, we could employ a station-level regression model instead of by station area type. In addition, the distance of influence by station-area built environment is likely to differ by station and service type. We used a half-mile buffer for consistency, but the rail services considered were varied (heavy rail, light rail, and trolley service).

Findings

This section discusses our findings following our research questions. We first introduce the results from descriptive analysis of the rail transit ridership. Then we present results from the statistical analyses examining associations between ridership change and built environment variables. Finally, we present the cluster analysis to create station-area types and compare ridership changes to LBS data changes around the station-area types.

Rail Transit Ridership Changes in COVID-19

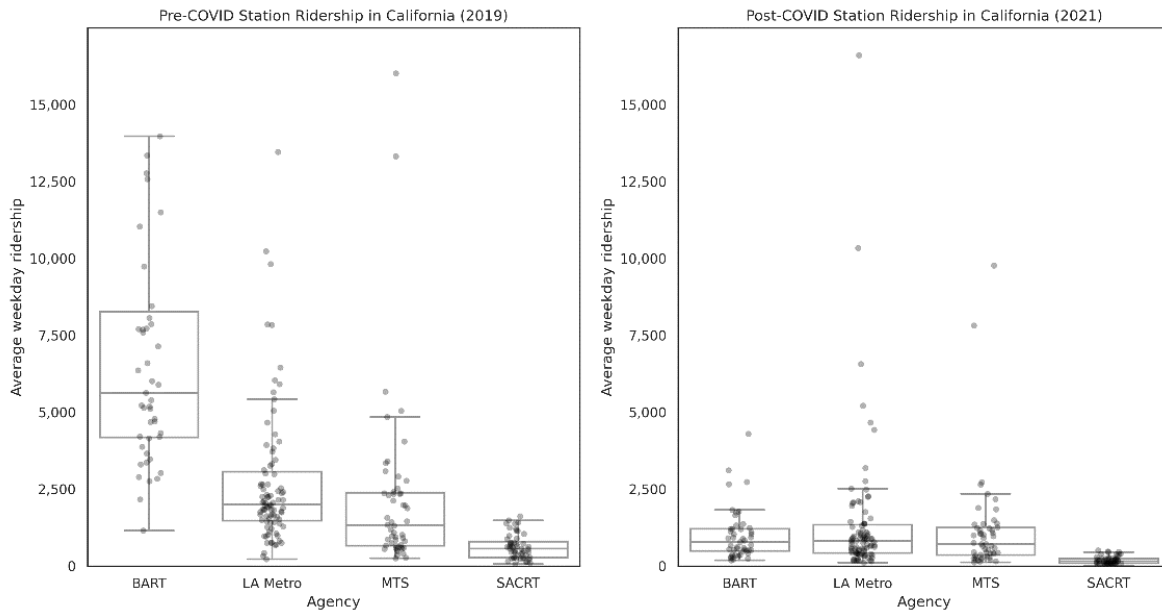


Figure 1. Pre-COVID and Post-COVID Ridership of Rail Transit Agencies in California for 242 Stations (left: February 2019; right: February 2021)

Figure 1 shows the distribution of station-level average weekday ridership in February 2019 and 2021. Across all 242 stations, the average weekday ridership declined from 3,615 to 1,007, a decrease of 72 percent. As expected, the pandemic had a significant impact on all four systems, which all experienced a significant drop in ridership. Before the pandemic, several BART stations, two MTS stations, and three LA Metro stations had more than 10,000 boardings. Post-pandemic, LA Metro had two stations and MTS had one station with an average weekday ridership exceeding 10,000.

Figure 2 shows the percent change in station-level average weekday ridership in the four systems. Notably, BART had the greatest decrease, with a more than 80 percent median decrease, followed by SACRT (67 percent), LA Metro (60 percent), and MTS (47 percent). The overall trend is consistent with findings by other

nationwide studies that transit ridership had dropped drastically due to COVID-19 (Bureau of Transportation Statistics 2021). Somewhat surprisingly, SACRT had one station (Richards Blvd) whose average weekday ridership increased by 35.64 percent from 101 to 137.

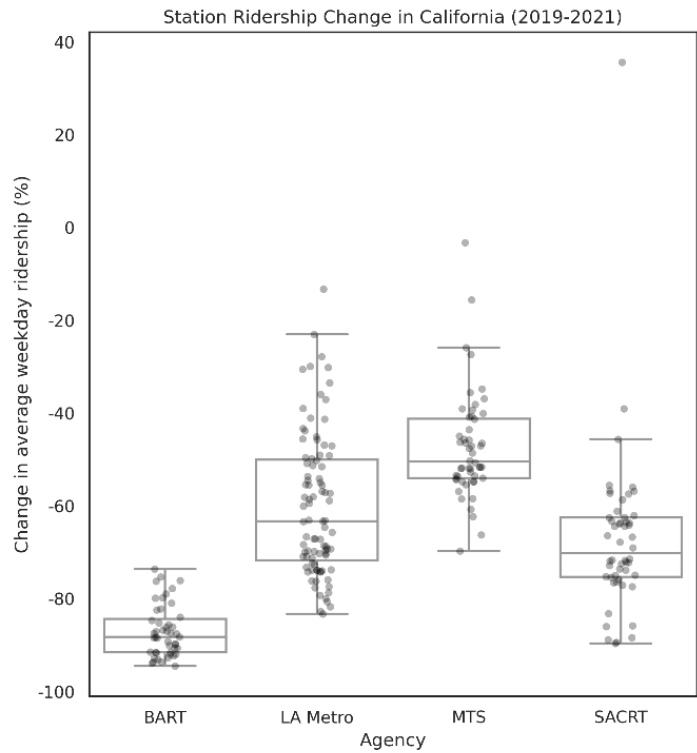


Figure 2. Percent Change in Station-Level Average Weekday Ridership of 242 Rail Transit Agencies in California

Figure 3 shows the geographic distribution of the stations for each transit system, as well as the percent change of average weekday ridership between February 2019 and 2021. BART’s decrease was fairly even system-wide, with slightly lower decreases at two terminal stations. By contrast, the other three systems had significant variation among transit lines, suggesting that station- and line-specific factors influence ridership change. In addition, this result points to potential error correlation within each line, and therefore we account for it by clustering the errors in our models by line.

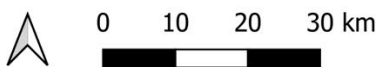
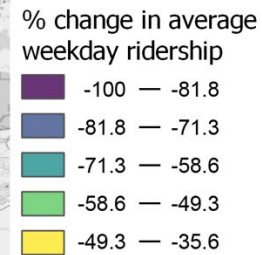
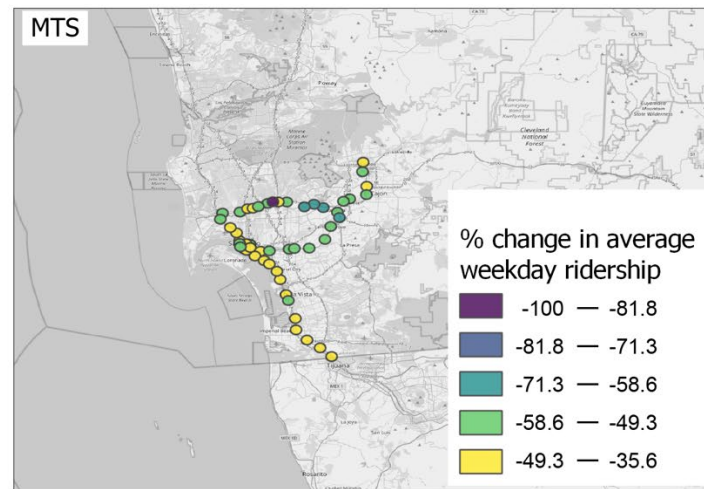
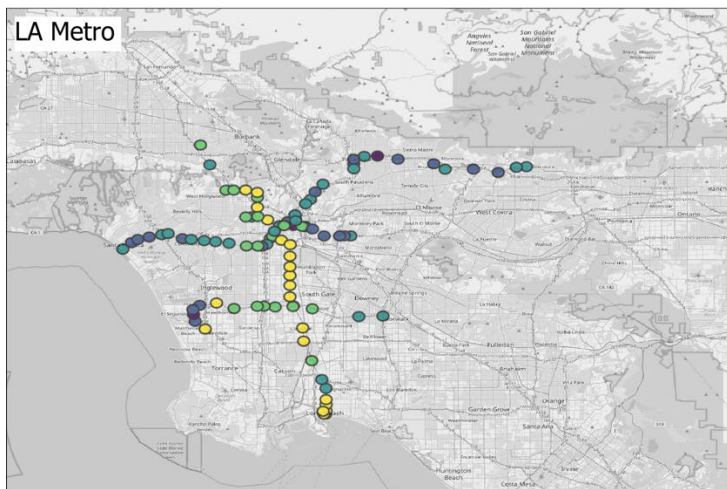


Figure 3. Percent Change of Average Weekday Ridership by Station between February 2019 and 2021 (n=242)

Associations between Rail Transit Ridership Changes and Station-Area Characteristics

Table 2 summarizes the dependent and independent variables in our final model. Variance inflation factors for station-area variables revealed high multicollinearity among low-, middle-, and high-income or wage groups, and employment densities by sector are highly correlated. We removed the middle-income/wage categories and kept low- and high-income/wage categories in the model. We also left out service, industrial, and public administration jobs densities.

Table 2. Summary Statistics of Dependent and Independent Variables (n = 242)

Variable	Mean	Std. Dev.	Min	Max
Percent change in average weekday ridership	-64.04	19.02	-93.63	35.64
Population density (persons per acre)	16.76	13.62	0.007	80.84
Number of zero-car households (1,000)	0.78	1.64	0	15.09
Number of low-income workers (home location) (1,000)	0.79	0.70	0.02	4.02
Number of high-income workers (home location) (1,000)	1.63	1.66	0.04	12.46
Number of low-wage jobs (1,000)	1.92	2.86	0.05	22.67
Number of high-wage jobs (1,000)	8.71	20.67	0.06	173.21
Retail job density (jobs per acre)	1.38	2.43	0.00	24.12
Office job density (jobs per acre)	3.62	12.14	0.002	123.59
Entertainment job density (jobs per acre)	3.41	6.42	0.00	44.88
Education job density (jobs per acre)	1.19	2.74	0.001	24.80
Health care job density (jobs per acre)	2.34	3.96	0.03	29.56
Pedestrian network density (miles per square mile)	18.90	7.08	4.08	57.67
Total road network density (miles per square mile)	28.37	9.41	7.64	74.66
Jobs within 45 minutes of auto travel time (1,000)	280.34	172.25	34.72	684.461
Jobs within 45 minutes of transit commute (1,000)	425.74	308.72	0.0	1193.71
Regional centrality index	0.63	0.17	0.11	0.94
Regional diversity index	0.41	0.16	0.00	0.81
Network betweenness centrality index	0.193	0.15	0.0	0.56
Within environmentally disadvantaged area (1: yes; 0: no)	0.421	0.459	0	1

Table 3 shows the results of the regression analysis. The plots of the residuals over space suggested that the correlation was strongly associated by line, specifically for MTS and LA Metro (see **Figure 4**). As a result, all models use standard errors clustered at the line level.

Table 3. Linear Regression Associations between Station-Area Characteristics and Percent Change in Average Weekday Ridership (Errors Clustered by Line)

	Dependent Variable: Percent Change in Average Weekday Ridership		
Variables	Coefficient		Std. Error
Population density (persons per acre)	0.19		0.18
Number of zero-car households (1,000)	-0.69		1.55
Number of low-income workers (home location) (1,000)	12.62	***	3.90
Number of low-wage jobs (1,000)	-0.98		2.51
Number of high-income workers (home location) (1,000)	-6.23	***	2.06
Number of high-wage jobs (1,000)	-0.29	**	0.13
Retail job density (jobs per acre)	1.93	*	1.03
Office job density (jobs per acre)	-0.08		0.27
Entertainment job density (jobs per acre)	1.18	**	0.47
Education job density (jobs per acre)	-0.05		0.48
Health care job density (jobs per acre)	-0.26		0.31
Pedestrian network density (miles per square mile)	-0.04		0.42
Total road network density (miles per square mile)	0.39		0.41
Jobs within 45 minutes of auto travel time (1,000)	0.02		0.02
Jobs within 45 minutes of transit commute (1,000)	-0.03	***	0.01
Regional centrality index	27.05		19.80
Regional diversity index	-3.09		5.86
Network betweenness centrality index	-1.90		16.57
Within environmentally disadvantaged area (1: yes; 0: no)	5.92		3.84
Intercept	-87.42	***	6.56
Observations	242		
R-squared	0.44		
Adjusted R-squared	0.39		
Residual standard error	14.89 (df = 222)		
F statistic	9.02*** (df = 19; 222)		

*p<0.1, **p<0.05, ***p<0.001

The coefficients suggest that station areas with more low-income workers experienced a smaller percent decrease in transit ridership, and that areas with more high-income workers or high-wage jobs tended to have significantly higher losses. Higher income residents and high-income jobs are similar in that they are often correlated to job flexibility in terms of remote work. In addition, areas with more retail and entertainment jobs

experienced lower ridership declines. Specifically, for every 1,000 additional low-income workers residing in a station area,² there was a 12.62 percentage increase in average weekday ridership. By contrast, for every 1,000 additional high-income workers residing in the station area,³ ridership was 6.23 percent lower. Similarly, an additional 1,000 high-wage jobs in a station area is also associated with 0.29 percent lower ridership. An increase of one retail job per acre is associated with a 1.93 percent higher ridership, while one entertainment job per acre was associated with a 1.18 percent increase. Station areas with higher job accessibility as measured by jobs within 45 minutes by transit tended to lose 0.03 percent more average weekday ridership. In a sensitivity analyses, our models were robust to the removal of the regional centrality index with coefficient magnitudes, and significance remaining unchanged for all variables except for network betweenness centrality, which became positive and highly significant. Because the model fit of the model shown in **Table 3** was much higher, we included those results here.

It is possible that the ridership changes were also reflecting transit service changes. We tested the correlation between service changes and ridership change by estimating a model that included a variable that measures service frequency changes (percent change in average hourly departure per station). Unsurprisingly, the result indicates a significant association between service frequency drops and ridership decreases. But, did low ridership cause cuts in transit service or vice versa, or both? Absent additional information on the reasons for cuts, it is impossible to ascertain what caused what. We surmise that it is likely that both transit cuts and low ridership each affected the other, which is the definition of an endogenous relationship. We therefore excluded the transit service variable from the final model shown in **Table 3**.

² Workers earning \$1,250/month or less, 2017.

³ Workers earning \$3,333/month or more, 2017.

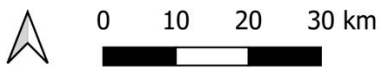
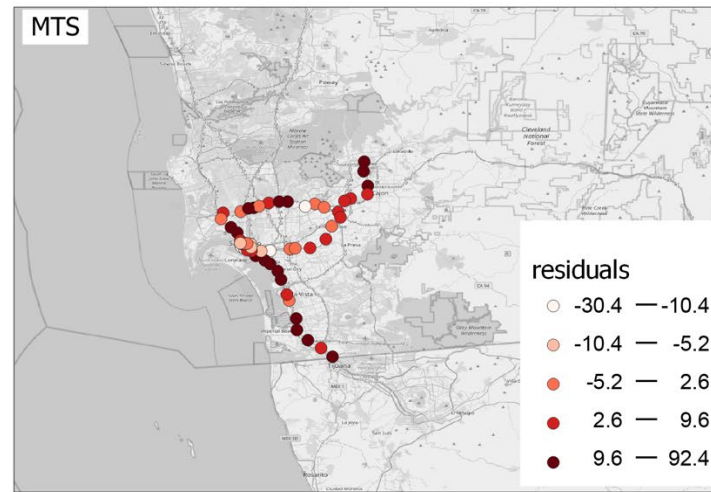
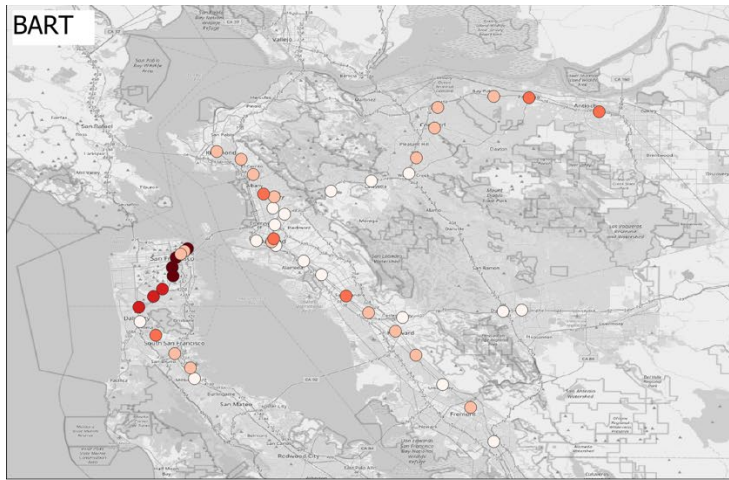


Figure 4. Model Residuals for Each Station by Transit System

Station-Area Activity Changes

The previous section identified station-area factors associated with changes in station ridership. In this section, we examine whether those changes were specific to transit ridership, or if they reflect broader drops in activity and visits to the station areas. We used LBS data to measure activity during February 2020 and February 2021. We identified 12,841 trips to 180 rail station areas in February 2020 (2.41 trips per person) and 7,890 trips in February 2021 (1.72 trips per person), an aggregate drop of 28.6 percent. Because not all station areas have LBS trip data, meaning that they didn't have any visits before and after, they were eliminated from the sample. This resulted in 62 fewer stations, for a total of 180 stations for the cluster analysis.

As **Figure 5** shows, at the station-area level, activity also decreased over time for most stations. However, activity at some stations increased noticeably (for visual simplicity, **Figure 5** excludes four stations with increases greater than 1,000 percent). Estimates of changes are especially sensitive when there were very few visits to a particular station. Some station areas had less than 100 visits in a month. Further, percent decreases are bound by 0, but increases can be much greater.

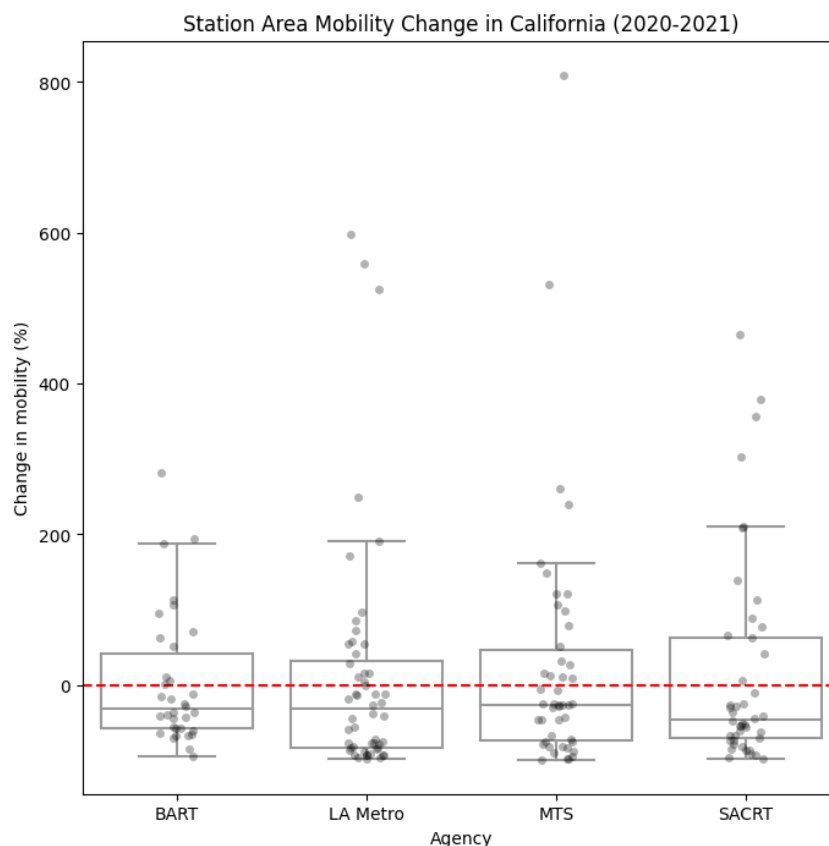


Figure 5. Percent Change in Station-Area Visits (n = 176; Four Outlying Observations Excluded)

The small number of visits to some individual stations led us to cluster station areas into a smaller number of station area types. This approach allows us to aggregate visits to their broader types and obtain more reliable estimates of activity changes. We used the same set of variables for the clustering as in the final regression model (**Table 3**), which includes 19 station-area characteristics for the 180 stations. We identified a total of 10 clusters across four transit systems among the 180 stations considered. **Figure 6** shows the location of stations among each type within the system.

BART and LA Metro stations were grouped into three station area types within each system, while SACRT and MTS stations were grouped into two types. For BART and LA Metro, the rule for determining the number of clusters suggested that they should have two or three station area types, closely followed by a three-type solution. Our own prior knowledge and experience with these station areas suggest that a three-type solution for each case was more appropriate.

The characteristics of stations belonging to each type are shown in **Table 4**. We labeled these station types “downtown,” “urban,” and “suburban” based on differences in built environment characteristics within each system. With the exception of LA Metro, all systems had their downtown station type representing the highest concentration of resident population, zero-car households and high-income residents who work; the highest concentration of jobs across sectors (retail, office, entertainment, education, and health care), high- and low-wage jobs; and the highest job accessibility by transit relative to the other types. A uniqueness in LA Metro types is that there is less balance between the location of jobs and housing. Specifically, relative to the downtown type, population density and the corresponding concentration of resident workers in the urban type is higher.

The coverage of the station types with environmentally disadvantaged areas varies widely. None of the BART downtown types overlap with disadvantaged communities, while 75 percent of SACRT, 25 percent of LA Metro, and 10 percent of MTS contained disadvantage areas.

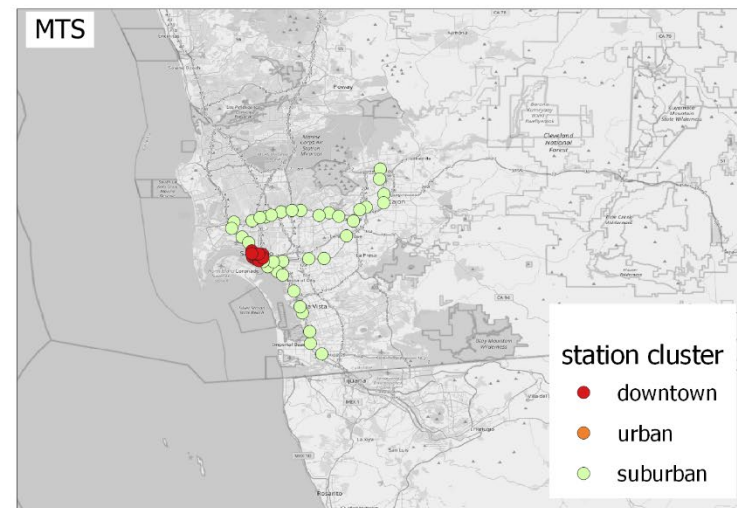
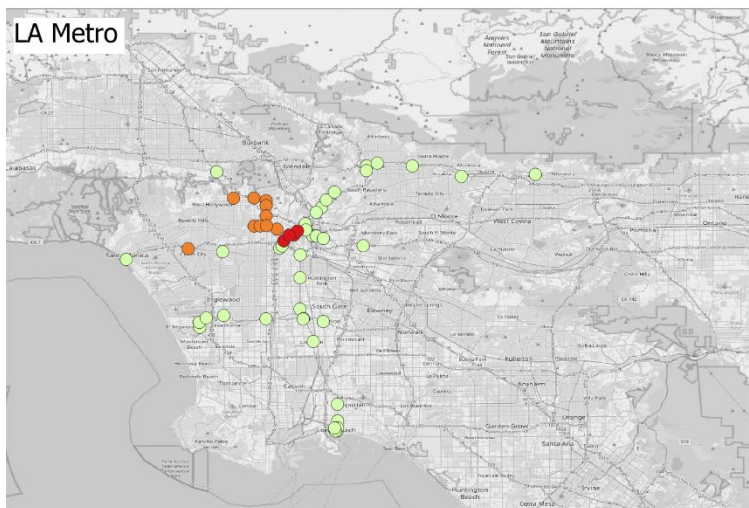
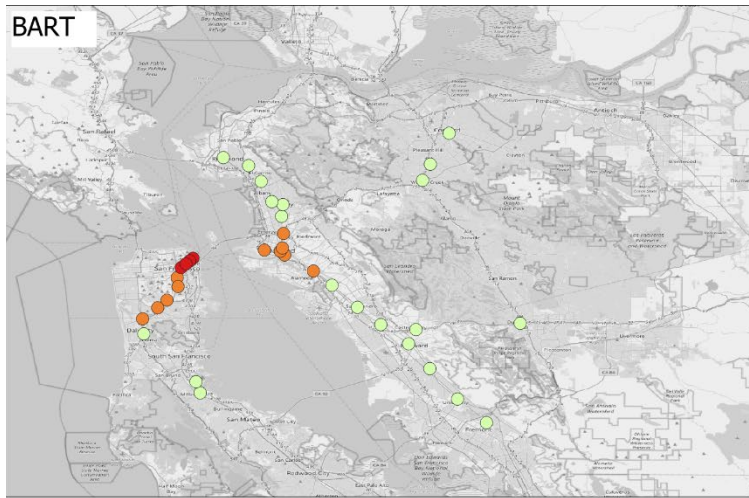
Despite these relative similarities, the station area types across systems are not directly comparable. A downtown stop in one system can be qualitatively different than a downtown type in another system. For example, the downtown BART type has the highest concentration of residents and jobs, far surpassing the downtown types of other systems. Similarly, the residential density of BART’s urban stop types is similar to LA Metro’s downtown figures. At the same time, LA Metro’s urban type stations have a higher concentration of low-income workers and zero-car households than BART’s urban type.

When assessing changes in ridership to changes in activity around the station area types, the “downtown” stations had a greater drop in ridership than the other stations and a much greater decrease in overall activity in the station area than other station types. Downtown stations and station areas suffered from both the largest ridership and activity decreases of all station types, respectively. Yet, the decreases in ridership were always greater, sometimes significantly so, than the decreases in activity. For example, changes among BART’s four downtown station area types diverged significantly, with a ridership loss of 90.8 percent and an activity

decrease of 40.9 percent. Meanwhile, Sacramento’s 16 downtown station area types had a ridership loss of 71.3 percent and a station area activity decrease of 64.1 percent

Among the four systems, stations exhibit similar patterns in terms of the association between changes in ridership and overall changes in activity. **Figure 7** depicts the percent decrease in activity to each station area type (y-axis) and ridership (y-axis) with a 45-degree line showing the same changes to both activity and ridership. The further away from the 45-degree line, the higher the discrepancy between both measures. All the systems are below the 45-degree line, meaning that they have higher decreases in ridership than in activity. Furthermore, the “downtown” stations (shown as circles) are closer to the origin, which means they experienced more ridership and mobility decreases than other station types. Other station types had similar levels of ridership decrease but much smaller activity decreases. The MTS stations exhibit less distinctive patterns among the station types, with all stations losing similar levels of ridership and activity. Notably, the only increases in activity were observed for 21 “suburban” station areas of BART and the 29 for SACRT.

Despite having the greatest ridership drop among the four systems examined, BART station areas did not lose as much station-area activity, implying that BART had a considerable share of former transit riders who opted to use other travel modes, such as driving, ride-hailing, walking, biking, or micromobility, to replace BART trips as the pandemic was waning. Because commute-type trips dominated BART ridership before the COVID pandemic, ridership decreased more and recovered much slower than the other systems (Wasserman & Taylor 2023). Remote work is more prevalent among high-wage jobs, making it harder for ridership to bounce back post pandemic. Areas with more high-wage jobs did have larger losses in the number of visits, whereas transit systems that carry more commute trips that shifted to remote work lost more ridership. Overall, ridership dropped more in areas with a greater number of high-wage jobs, such as downtown BART, SACRT, and LA Metro, whereas suburban or lower-density stations had lower decreases in ridership, which also had lower decreases, and sometimes increases, in the number of visits to the station areas, except for LA Metro.



station cluster
 ● downtown
 ● urban
 ● suburban

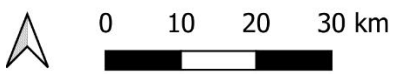


Figure 6. Station Area Types by System Based on Station-Area Characteristics

Table 4. Mean Values of Station-Area Characteristics and Percent Change in Ridership and Number of Visits per Capita by Cluster (n = 180)

	BART			SACRT		LA Metro			MTS	
	Downtown	Urban	Suburban	Downtown	Suburban	Downtown	Urban	Suburban	Downtown	Suburban
Clusters built environmental characteristics										
Number of stations in cluster	4	11	21	16	29	4	10	39	10	36
Population density (persons per acre)	51.73	30.63	15.72	10.59	7.01	27.97	51.41	19.36	21.61	10.61
Number of zero-car households (1,000)	9.58	1.90	0.39	1.04	0.11	2.83	2.74	0.54	1.72	0.18
Number of low-income workers (home location) (1,000)	2.55	1.40	0.63	0.43	0.33	1.33	2.85	0.92	0.83	0.51
Number of high-income workers (home location) (1,000)	8.69	4.57	2.01	1.20	0.64	3.14	3.88	1.33	2.54	0.90
Number of low-wage jobs (1,000)	16.68	2.48	0.97	3.73	0.44	11.18	3.05	1.52	5.10	1.06
Number of high-wage jobs (1,000)	115.66	14.14	2.96	30.66	1.49	70.11	5.83	5.06	15.75	1.89
Jobs within 45 minutes of auto travel time (1,000)	265.92	219.75	148.85	184.19	128.58	669.23	538.47	463.19	207.24	166.45
Jobs within 45 minutes of transit commute (1,000)	1106.67	769.63	362.03	475.66	143.70	1052.37	870.01	575.71	265.65	178.10
Regional centrality index	0.76	0.67	0.45	0.82	0.60	0.88	0.71	0.61	0.81	0.69
Regional diversity index	0.35	0.41	0.42	0.40	0.42	0.35	0.43	0.38	0.60	0.42
Retail job density (jobs per acre)	16.51	1.36	1.20	0.95	0.36	4.30	2.23	1.28	1.84	1.07
Office job density (jobs per acre)	77.95	5.20	1.83	3.23	0.69	28.10	2.75	2.56	6.23	0.59
Entertainment job density (jobs per acre)	33.94	3.14	1.29	7.18	0.34	24.11	4.67	2.24	15.93	1.48
Education job density (jobs per acre)	8.94	4.72	0.85	0.50	0.48	7.61	1.29	0.88	1.29	0.94
Health care job density (jobs per acre)	15.09	3.70	1.80	1.96	0.81	10.86	9.35	2.45	1.31	1.34
Network betweenness and centrality index	0.37	0.36	0.15	0.30	0.19	0.35	0.08	0.13	0.10	0.30
Total road network density (miles per square mile)	38.21	35.73	26.21	37.04	20.45	34.28	26.28	29.95	51.93	26.57
Pedestrian network density (miles per square mile)	20.16	23.74	19.70	22.22	14.80	16.24	19.75	20.24	32.38	16.77
Within environmentally disadvantaged area (1: yes; 0: no)	0.00	0.36	0.10	0.75	0.34	0.25	0.50	0.64	0.10	0.33
Cluster ridership and trip performance										

	BART			SACRT		LA Metro			MTS	
Percent change in aggregate average weekday ridership	-90.75	-86.89	-86.92	-71.25	-68.67	-64.79	-50.25	-63.76	-47.04	-46.51
Percent change in number of per capita visits to station area cluster (20–21)	-40.94	-29.79	1.77	-64.14	13.46	-54.04	-3.15	-35.61	-19.96	-18.90
Number of per capita visits to station area type, February 2020	0.2630	0.1809	0.2463	0.3054	0.2379	0.0707	0.1111	0.2816	0.1998	0.3831
Number of per capita visits to station area type, February 2021	0.1554	0.1270	0.2507	0.1095	0.2699	0.0325	0.1076	0.1813	0.1599	0.3107

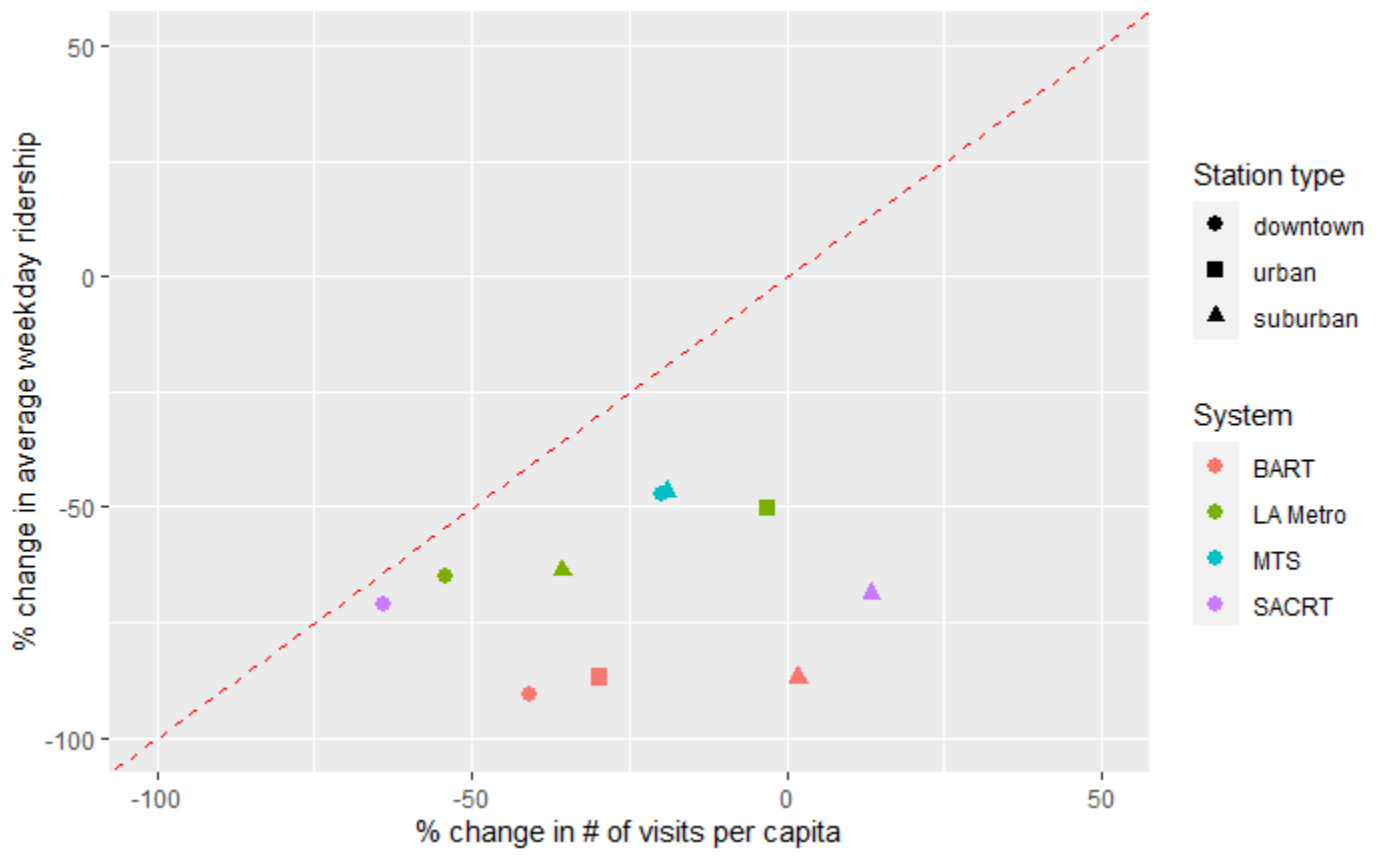


Figure 7. Relationship between Percent Change in Average Weekday Ridership and Number of per Capita Station-Area Visits

Conclusions

The COVID-19 pandemic has had a significant impact on public transit ridership in the United States, especially for rail transit. Land use, development density, and the pedestrian environment are strongly associated with station-level transit ridership. This study examined how these characteristics affect transit ridership pre- and post-COVID and how they differ across station types based on longitudinal data for 242 rail stations belonging to Bay Area Rapid Transit, San Diego Metropolitan Transit System, Sacramento Regional Transit, and LA Metro rail stations between 2019 and 2021. The pandemic had a significant impact on all four systems, with an average decrease of 72 percent—BART had the greatest decrease, and MTS had the lowest decrease. The overall trend is consistent with findings by other nationwide studies that transit ridership had dropped drastically due to COVID-19 (Bureau of Transportation Statistics 2021), although more recent data suggests that ridership has increased but not up to the 2019 levels. Spatially, there was variation in the changes in ridership of each system, with most decreases appearing specific to individual stations or entire lines.

Our examination of the station-area characteristics associated with ridership changes confirmed expectations about the role that certain occupations, workplaces, and residential locations have in determining the post-pandemic use of transit generally and specific transit stops in particular. Areas with more low-income workers and more retail or entertainment jobs had lower ridership declines, while areas with more high-income workers, high-wage jobs, or transit-accessible jobs had higher ridership losses. Additionally, our sensitivity analysis showed that ridership drops during the pandemic had a strong correlation with transit service, although it is difficult to ascertain which came first.

Further, we found that ridership decreased more than station-area activity, as surmised from cell phone data traces, implying that some former transit riders stopped traveling altogether, whereas other former riders switched to other modes of transportation to reach the same destination. Downtown stations also had a more dramatic decrease in ridership than other stations. Whether this trend will translate into more permanent work patterns, as well as changes in car-ownership, remains to be determined.

One spatial consequence is that rail transit services oriented toward serving the work commute, especially core station areas with jobs for higher income workers, will continue to have an uneven recovery. It is likely that those locations will also have a real estate readjustment to better match the supply of class A office space with existing demand. As a result, shifting rail transit services to non-commute travel can be a promising strategy. Most research suggests that travelers are sensitive to service changes, especially individuals traveling during off-peak hours and for non-work purposes. Improving service quality during the off-peak and orienting to non-work destinations could help bring ridership back.

The changes documented in this study—and the station-area environmental characteristics associated with those changes—reinforce the pre-pandemic pattern of California transit riders being fewer and poorer over time. For rail transit, the decrease in ridership translates into lower fare revenues and augurs chronic funding

shortfalls. It is tempting to consider cuts to frequency or span of service as a way to realign revenues with costs, but this could trigger a spiral of mutually reinforcing cuts and ridership losses. Considering other sources of funding to sustain rail transit, strategizing to reinvent and reinforce downtowns as destinations, and appealing to non-commute riders are possible short-term strategies to support rail transit.

References

- Abdel-Salam, G. H. 2014. *Active Travel, Built Environment and Transit Access: A Micro-Analysis of Pedestrian Travel Behavior* [Ph.D., University of California, Irvine].
<https://search.proquest.com/pqdtglobal/docview/1639700653/abstract/B3DB055A423E4D78PQ/1>
- Andersson, D. E., Shyr, O. F., and Yang, J. 2021. Neighbourhood effects on station-level transit use: Evidence from the Taipei metro. *Journal of Transport Geography*, 94, 103127.
<https://doi.org/10.1016/j.jtrangeo.2021.103127>
- Brandes, U. 2008. On variants of shortest-path betweenness centrality and their generic computation. *Social Networks*, 30(2), 136–145. <https://doi.org/10.1016/j.socnet.2007.11.001>
- Bureau of Transportation Statistics. 2021. *COVID-19 Takes a Bite out of 2020 Passenger Transportation*.
<https://www.bts.gov/data-spotlight/covid-19-takes-bite-out-2020-passenger-transportation>
- Cervero, R. and Murakami, J. 2008. *Rail + Property Development: A model of sustainable transit finance and urbanism*. <https://escholarship.org/uc/item/6jx3k35x>
- Doyle, T. 2023. Public Transportation Ridership Rises to More than 70 Percent of Pre-Pandemic Levels. *American Public Transportation Association*. <https://www.apta.com/news-publications/press-releases/releases/public-transportation-ridership-rises-to-more-than-70-percent-of-pre-pandemic-levels>
- Ewing, R. and Cervero, R. 2010. Travel and the Built Environment: A Meta-Analysis. *Journal of the American Planning Association*, 76(3), 265–294. <https://doi.org/10.1080/01944361003766766>
- Freeman, L. C. 1977. A Set of Measures of Centrality Based on Betweenness. *Sociometry*, 40(1), 35.
<https://doi.org/10.2307/3033543>
- Guzman, L. A. and Gomez Cardona, S. 2021. Density-oriented public transport corridors: Decoding their influence on BRT ridership at station-level and time-slot in Bogotá. *Cities*, 110, 103071.
<https://doi.org/10.1016/j.cities.2020.103071>
- Kamargianni, M., Georgouli, C., Tronca, L. P., and Chaniotakis, M. 2022. Changing transport planning objectives during the Covid-19 lockdowns: Actions taken and lessons learned for enhancing sustainable urban mobility planning. *Cities*, 131, 103873. <https://doi.org/10.1016/j.cities.2022.103873>
- Kim, J. and Loh, T. H. 2021. To recover from COVID-19, downtowns must adapt. *Brookings*.
<https://www.brookings.edu/research/to-recover-from-covid-19-downtowns-must-adapt>
- Lee, K.-S. and Eom, J. K. 2023. Systematic literature review on impacts of COVID-19 pandemic and corresponding measures on mobility. *Transportation*. <https://doi.org/10.1007/s11116-023-10392-2>

- Li, M., Sheng, H., Irvin, J., Chung, H., Ying, A., Sun, T., Ng, A. Y., and Rodriguez, D. A. 2022. Marked crosswalks in US transit-oriented station areas, 2007–2020: A computer vision approach using street view imagery. *Environment and Planning B: Urban Analytics and City Science*, 239980832211121. <https://doi.org/10.1177/23998083221112157>
- Macqueen, J. 1967. Some Methods for Classification and Analysis of Multivariate Observations. *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability*, 1, 281–297.
- Parker, M. E. G., Li, M., Bouzaghane, M. A., Obeid, H., Hayes, D., Frick, K. T., Rodríguez, D. A., Sengupta, R., Walker, J., and Chatman, D. G. 2021. Public transit use in the United States in the era of COVID-19: Transit riders’ travel behavior in the COVID-19 impact and recovery period. *Transport Policy*. <https://doi.org/10.1016/j.tranpol.2021.07.005>
- Rodríguez, D. A., Brisson, E. M., and Estupiñán, N. 2009. The relationship between segment-level built environment attributes and pedestrian activity around Bogota’s BRT stations. *Transportation Research Part D: Transport and Environment*, 14(7), 470–478. <https://doi.org/10.1016/j.trd.2009.06.001>
- Rodríguez, D. A. and Kang, C.-D. 2020. A typology of the built environment around rail stops in the global transit-oriented city of Seoul, Korea. *Cities*, 100, 102663. <https://doi.org/10.1016/j.cities.2020.102663>
- Ryan, S. and Frank, L. 2009. Pedestrian Environments and Transit Ridership. *Journal of Public Transportation*, 12(1), 39–57. <https://doi.org/10.5038/2375-0901.12.1.3>
- Taylor, B., Blumenberg, E., Wasserman, J., Garrett, M., Schouten, A., King, H., Paul, J., and Ruvolo, M. 2020. *Transit Blues in the Golden State: Analyzing Recent California Ridership Trends*. <https://doi.org/10.17610/T67W2Z>
- Urban Institute. 2021. *Transit Ridership Dropped at Heavy Rail Stations during the COVID-19 Pandemic, but Ridership Change Depended on Neighborhood Characteristics*. <https://www.urban.org/urban-wire/transit-ridership-dropped-heavy-rail-stations-during-covid-19-pandemic-ridership-change-depended-neighborhood-characteristics>
- Vergel-Tovar, C. E. and Rodriguez, D. A. 2018. The ridership performance of the built environment for BRT systems: Evidence from Latin America. *Journal of Transport Geography*, 73, 172–184. <https://doi.org/10.1016/j.jtrangeo.2018.06.018>
- Wasserman, J. L. and Taylor, B. D. 2023. State of the BART: Analyzing the Determinants of Bay Area Rapid Transit Use in the 2010s. *Transportation Research Part A: Policy and Practice*, 172, 103663. <https://doi.org/10.1016/j.tra.2023.103663>
- Willson, R. 2005. Parking Policy for Transit-Oriented Development: Lessons for Cities, Transit Agencies, and Developers. *Journal of Public Transportation*, 8(5), 79–94. <https://doi.org/10.5038/2375-0901.8.5.5>

