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FINAL REPORT
FEBRUARY 2024

Predicting Travel and Congestion in Post-Pandemic America

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Technical Report Documentation Page

1. Report No.	**2. Government Accession No.**	**3. Recipient's Catalog No.**	
4. Title and Subtitle Predicting Travel and Congestion in Post-Pandemic America: Phase 2 Implications for Urban Mobility		**5. Report Date** February 2024	
		6. Performing Organization Code	
7. Author(s) Mahim Khan, Vivek Gupta, Dunn Brian, Luke Albert		**8. Performing Organization Report No.**	
9. Performing Organization Name and Address Texas A&M Transportation Institute 3135 TAMU College Station, TX 77843		**10. Work Unit No. (TRAIS)**	
		11. Contract or Grant No. 69A3551947136; 79075-00-SUB B	
12. Sponsoring Organization Name and Address U.S. Department of Transportation University Transportation Centers 1200 New Jersey Avenue, SE Washington, DC 20590 United States National Institute for Congestion Reduction 4202 E. Fowler Avenue Tampa, FL 33620-5375 United States		**13. Type of Report and Period Covered** Final Report (May 1, 2022 to February 29, 2024)	
		14. Sponsoring Agency Code	
15. Supplementary Notes			
17. Key Words Transit, Passenger Miles Travelled, Delay, Vehicle Miles Travelled		**18. Distribution Statement** Unrestricted	
19. Security Classification (of this report) Unclassified.	**20. Security Classification (of this page)** Unclassified.	**21. No. of Pages** 43	**22. Price**

16. Abstract

The COVID-19 pandemic has had a profound impact on travel behavior, particularly in the realm of public transportation. This report aims to assess the long-term effects of the pandemic on the transportation system, with a focus on transit ridership and congestion in dense urban areas. The research conducted in this project, including the analysis of transit data, estimation of daily passenger miles traveled, and evaluation of mode shares, provides valuable insights for understanding the effects of the pandemic on transportation systems. The research team categorized ten modes of public transportation into four categories: bus, heavy rail, light rail, and monorail. Top metropolitan areas in the U.S. were further subdivided into very large, large and medium based on the transit usage. Overall larger metros with extensive transit systems, such as New York and Chicago, are expected to recover faster compared to medium-sized metros that rely primarily on light rail or buses for transportation. This is because the availability of more transit options encourages additional commuters to use public transportation, reducing congestion on roads.

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Executive Summary

The COVID-19 pandemic has had a profound impact on travel behavior, particularly in public transportation. This report assesses the long-term effects of the pandemic on the transportation system, with a focus on transit ridership and congestion in dense urban areas. Concerns have arisen regarding the ability of transit ridership to fully recover due to lingering fears of close physical contact and the availability of alternative commuting options. Additionally, the rise of remote work has contributed to a decline in transit ridership, further casting doubt on the ability of transit systems to regain pre-pandemic ridership levels.

Phase 1 of this research project explored the psychological factors contributing to low transit ridership post-COVID. Through surveys and immersive virtual reality experiences, the research team sought to understand the fears and anxieties of individuals regarding COVID-19 and transit travel. The findings revealed that a significant portion of respondents reduced their use of transit during and after the pandemic due to higher stress levels and fear of COVID-19. Factors such as household size, income, comfort on crowded buses, fear of contracting the virus, age, and gender were found to be significantly linked to the decline in transit use.

Phase 2 of this project, presented in this report, focuses on exploring the impact of reduced transit use on the efficiency of the transportation roadway system, particularly in dense urban areas. The research team utilized large-scale traffic and transit data to forecast congestion levels post-pandemic. The findings from this analysis provide valuable insights for policymakers, urban planners, and transportation agencies in developing strategies to manage congestion, improve public transit, and adapt infrastructure to meet changing transportation needs.

The report emphasizes several factors that influence the change in travel behavior. One key factor is the rise in work-from-home policies. The increased prevalence of remote work has led to a reevaluation of commuting patterns and transportation preferences. Despite the high cost of ownership, there has been an increase in the sales of automobiles, and vehicle miles traveled (VMT), indicating a shift towards private vehicles as individuals seek greater flexibility and perceived safety in their travel arrangements.

The complex dynamics resulting from increased vehicle miles traveled, auto ownership, and reduced transit ridership pose significant challenges for traffic congestion. The research conducted in this project, including the analysis of transit data, estimation of daily passenger miles traveled, and evaluation of mode shares, provides valuable insights for understanding the effects of the pandemic on transportation systems.

The research team categorized ten modes of public transportation into four categories: bus, heavy rail, light rail, and monorail. This categorization enabled a more comprehensive analysis of travel behavior patterns. By estimating daily passenger miles traveled for each mode, the team identified the top 18 metropolitan areas with the highest daily transit passenger miles traveled for further analysis.

The top 18 metropolitan areas were further subdivided into very large, large, and medium based on transit usage. Metros with a population of more than 8 million were classified as very large, metros with a population between 3 and 6 million were classified as large, and metros with a population of less than 3 million were classified as medium-sized.

The report assessed congestion and its impact on travel through metrics such as delay and the travel time index (TTI). As per the report, congestion levels in many U.S. metropolitan areas have gradually approached or exceeded pre-pandemic levels, presenting substantial challenges for policymakers and urban planners.

Excess fuel consumption resulting from congestion emerged as a notable concern. The report analyzed annual excess fuel consumption and excess fuel consumed per commuter, shedding light on the environmental and economic consequences of traffic congestion. Metropolitan areas such as Los Angeles and New York exhibited significant levels of excess fuel consumption.

Transit mode shares were analyzed in various metropolitan areas, highlighting the varying transportation preferences. The findings reveal a substantial decline in ridership across all modes of public transportation due to the COVID-19 pandemic. Heavy rail and bus modes exhibited greater resilience compared to light rail. In large metros like New York, heavy rail emerged as the primary mode of transit, while Los Angeles had a significant bus mode share. Medium-sized metro areas heavily depend on roads for transportation, and in comparison to very large and large metros, they are witnessing a faster recovery in bus usage. Despite this, there have been significant challenges in public transit ridership in these areas. The report underscores the importance of understanding these mode share variations for effective urban transportation planning.

The report also evaluates the impact of work-from-home (WFH) on changing travel patterns. The results indicate that while delays are nearing 2019 levels, their distribution throughout the day has undergone changes compared to the pre-pandemic period. While evening peak congestion is reaching pre-pandemic levels, morning peak congestion is still lower, showing that commute patterns have changed. There has been a noticeable rise in mid-day congestion, and weekends are now experiencing higher levels of commute compared to the pre-pandemic period.

In conclusion, the report underscores the significant impact of the COVID-19 pandemic on travel behavior, public transit ridership, remote work, congestion levels, and fuel consumption. It highlights the challenges that accompany public transit operations, mitigates the lingering transportation effects of the pandemic, addresses congestion challenges, and looks for sustainable transportation opportunities. The comprehensive analysis and findings presented in this report provide valuable insights for policymakers, urban planners, and transportation stakeholders, enabling informed decision-making and the improvement of urban transportation systems.

Chapter 1. Introduction

COVID-19 has affected travel behavior in many ways. Changes include a predictable reduction in overall travel and even larger reductions in transit travel, carpooling, and travel on toll facilities. Now, three years into the pandemic, we see signs of long-term impacts on the transportation system. What happens to travel and congestion once we return to a 'new normal'?

There are concerns that transit ridership may not fully recover due to the fear of close physical contact in public settings and the availability of alternative commuting or traveling options. Furthermore, the rise of remote work could contribute to a decline in transit ridership. This raises doubts about whether transit systems will be able to regain their pre-pandemic ridership levels. Therefore, this potential change may cause increased congestion in densely populated metropolitan areas where transit was once a major mode of mobility. Moreover, commute-dependent toll road and managed lane traffic may not experience a significant rebound, leading to inefficient use of road space and revenue shortfalls.

The low ridership in public transportation persists despite the high cost of vehicle ownership and high fuel costs. One of the primary deterrents that came out in the phase 1 study was the fear of contracting a virus. This was studied in the first phase of this project, where the research team explored the psychological factors responsible for low transit ridership post-COVID. This was done by conducting a survey measuring the stress level of the travelers using Galvanic Skin Response (GSR) and facial expressions along with self-reported responses to the survey. In order to get a deeper understanding of how individuals see the fear and anxiety of COVID-19 in the context of near-future transit travel, an immersive virtual reality (V.R.) environment was employed to replicate the transit experience. The results from the survey found that approximately 41% of respondents reduced their use of transit after the pandemic declaration in March 2020, and 45.5% stated they were less willing to use transit in the future, even after the pandemic is over. Such respondents reported higher average stress levels and more fear of COVID-19. A Random Forest Classification Model and a SHAP Value Plot were used to identify factors relevant to the stated reduced transit use for those travelers who were frequent transit users before the pandemic. The main factors linked to the reported decline in transit use were the size and yearly income of the household, one's degree of comfort on a crowded bus, one's fear of catching COVID-19 or danger of doing so, as well as one's age and gender. Therefore, in addition to telecommuting and mode shifts caused by the pandemic, transit agencies must overcome the stresses and fears that the commuters have related to COVID-19 for ridership to return to pre-pandemic levels.

A nearly identical survey was conducted in the human behavior laboratory (HBL) at Texas A&M University, where respondent stress levels were measured while taking the survey. The findings from this survey revealed that almost half of the respondents, 46%, decreased their use of public transportation after the pandemic was declared in March 2020, and nearly a quarter, 22.5%, stated they would use transit less even after the pandemic ended. When analyzing the peak stress events, it was found that both the first-perspective videos of a crowded bus stop and a crowded bus ride caused stress in a majority of participants. Respondents who did not show any stress were more likely to not change their transit use. The findings from Phase 1 will help the transit agencies and policymakers to understand the perception of the commuters and strategize to overcome the barriers to transit use.

It is now vital to understand the impact of reduced transit use on the overall efficiency of the transportation roadway system, particularly in dense urban areas. Therefore, Phase 2 of this project assesses congestion post-pandemic using large-scale traffic and transit data. Phase 1 of this project was completed in 2022, and the changes in travel and the potential recovery rates for the travel modes were identified. For this Phase 2 effort, the findings from Phase 1 along with large-scale traffic and transit data were used to predict congestion and travel in a new normal. The Urban Mobility Report (UMR) (Schrank et al., 2021) has evaluated the congestion in urbanized areas across the U.S. for several decades. The UMR data set provided the foundations to apply the findings from Phase 1 to existing urban measurement resources. Phase 2 objectives include:

- Measure the real-world impacts of the new modal choices as a result of the COVID-19 pandemic. Such measures may include the cost of delay in an urban system, the financial impacts to urban transit systems, and the environmental impacts related to these changes.

- Provide a nationwide assessment of the impact of COVID-19 on transportation and perform a detailed analysis of congestion and public transportation impacts in 18 urban areas in a new normal. These results will assess impacts on urban areas and allow for national transportation policy considerations.

- Application of the research that will provide insight to state departments of transportation, metropolitan planning organizations, and other agencies to better implement their travel demand management resources and plan for future modal demand.

Chapter 2. Background

Since the beginning of 2020, COVID-19 has spread throughout the world, causing unprecedented economic harm and human casualties. Like other businesses, the U.S. transportation sector has been highly impacted by the pandemic. The concern of COVID-19 spreading led to several policy changes, including social distancing and work-from-home, which in turn impacted public transit ridership. To ensure the enforcement of social distancing, many metros curtailed vehicle capacity for public transportation. One month into the pandemic saw an 80% reduction in transit use and a 40% reduction in Passenger VMT (Figure 1). Figure 1 shows relative change in different modes of travel compared to pre-COVID levels. By October 2020, passenger VMT had recovered, but public transit ridership was still 60% less than in the pre-COVID levels.

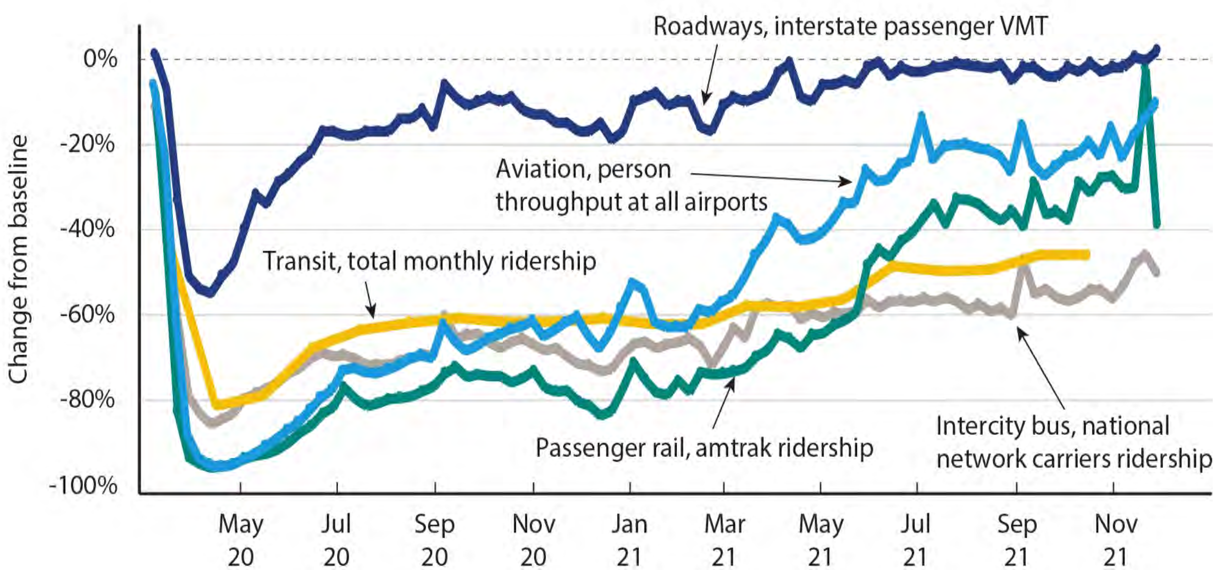

Figure 1. Monthly Percent Change in Passenger Travel from 2019 (Source: BTS)

One of the main factors contributing to lower transit ridership has been the widespread implementation of work-from-home policies. Because of COVID-19, several organizations (e.g., Amazon, Facebook, Salesforce, Siemens, Microsoft, Twitter, and Aetna) implemented work-from-home (WFH) policies (Howington, 2020), which were then resumed in Spring 2021 as the COVID-19 outbreak slowed down. For instance, in May 2021, Google unveiled a hybrid return-to-work plan with choices for both remote and in-office employment (Kelly, 2021). The average number of Americans who spend their days at home rose from 58 to 68 million in 2019 to 94.5 million in March and has remained much higher than in 2019. The trends of work from home from 2019 to March 2022 are depicted in Figure 2, which is a nationwide statistic. Seventy million people were still working from home in March 2022, a statistic that was at least 10 million greater than in 2019. Figures 2 and 3 show the trends in the number of people staying home across the country as of April 2021.

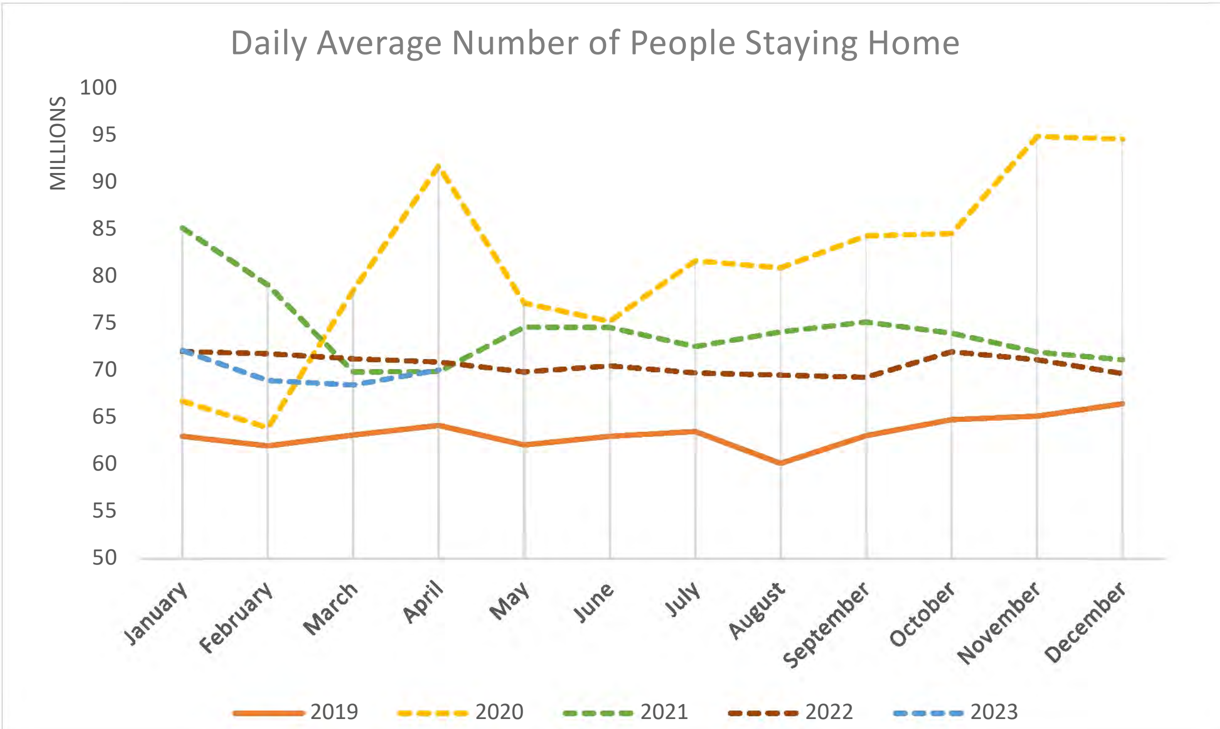

Figure 2. Number of People Staying Home

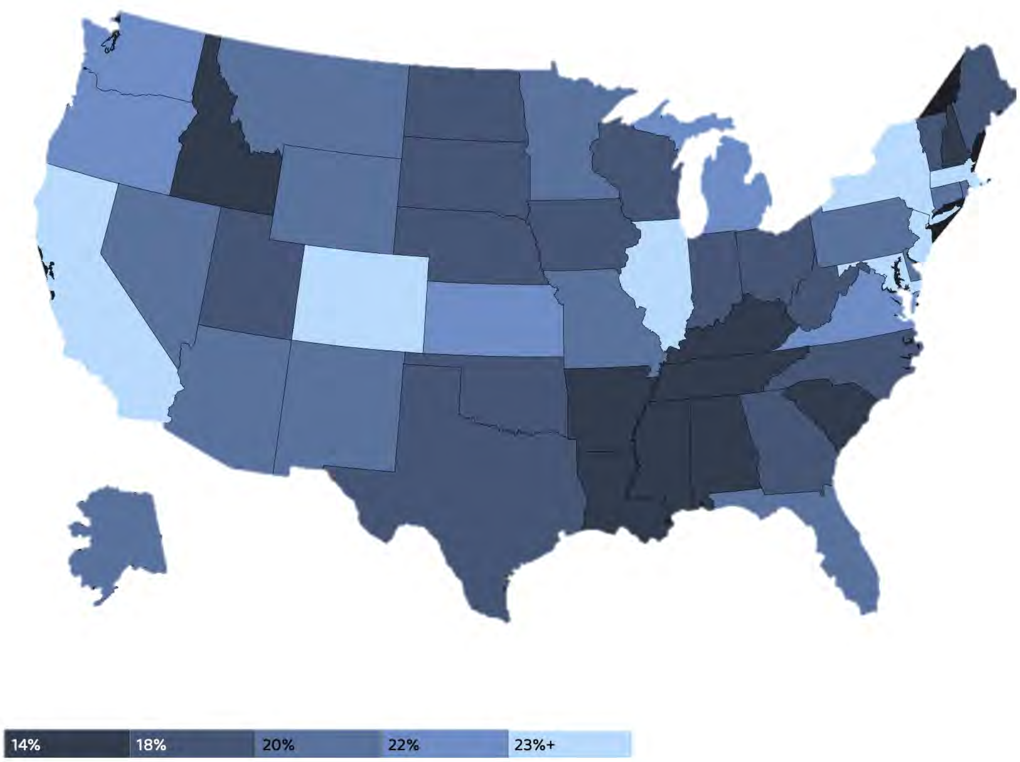

Figure 3. Percent of People Staying Home (Source: https://data.covid.umd.edu)

This increase in remote work has not only influenced transit ridership but has also prompted a reevaluation of commuting patterns and transportation preferences. There is an increasing interest in alternatives to transit mode, notably private vehicles. This shift is evident in the rising sales of automobiles (Figure 4), as people seem to seek greater flexibility, control, and perceived safety in their travel arrangements.

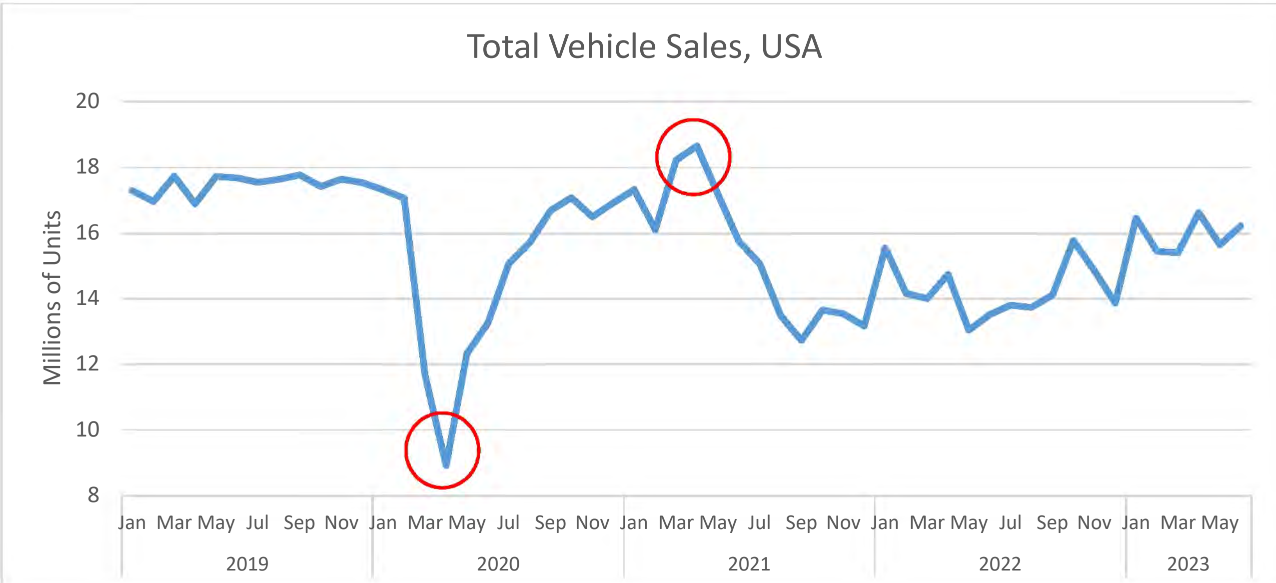

Figure 4. Monthly Car Sales in USA (Source: https://fred.stlouisfed.org)

The rising cost of car ownership, including insurance, fuel, maintenance, and other expenses, has not deterred the increasing sales of automobiles. Despite these escalating costs, the demand for cars has remained robust. In fact, the average new-vehicle transaction price has seen a significant surge, reaching $48,763(28% increase) according to Kelley Blue Book, compared to the pre-pandemic average of $37,876. Furthermore, the annual cost of owning a car in 2022 rose to $10,728 from $9,666 in 2021. This increase in ownership costs is part of a larger trend observed over the past two decades, with a notable rise in variable costs (Figure 5). These factors contribute to the overall financial burden associated with private vehicle ownership.

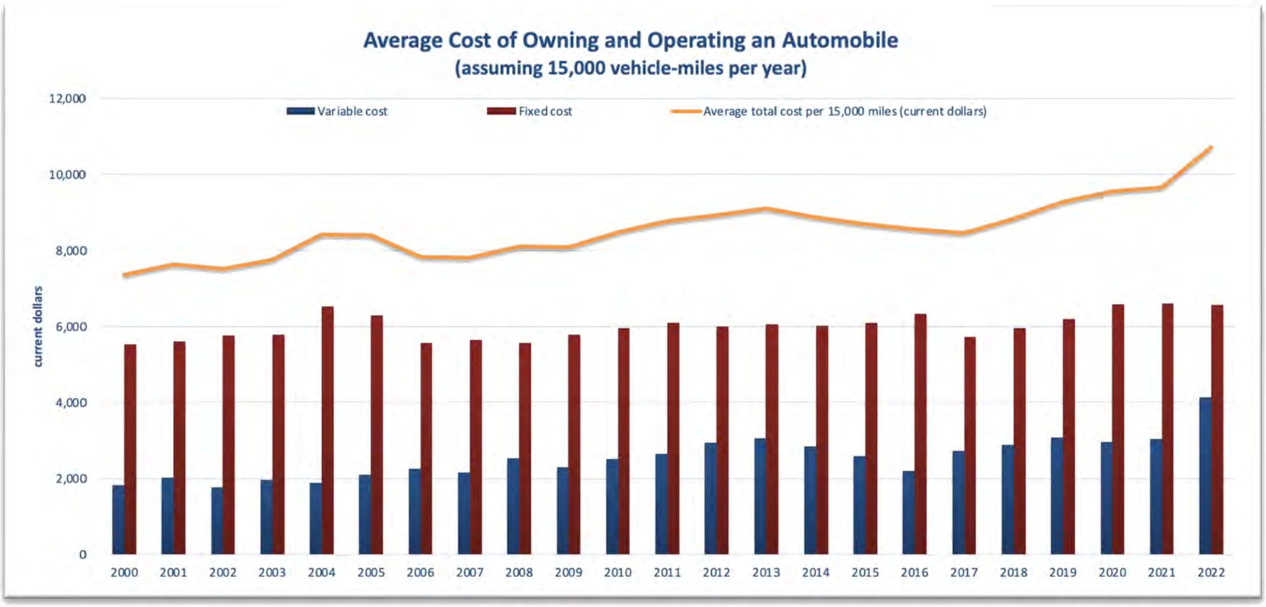

Figure 5. Cost of Car Ownership in USA (Source: Bureau of Transportation Statistics, 2022)

The factors mentioned, such as increased Vehicle Miles Traveled (VMT) and auto ownership despite rising costs, along with lower transit ridership, highlight the complex dynamics influencing transportation choices in the aftermath of the COVID-19 pandemic. The long-term sustainability of increased VMT and auto ownership raises concerns about traffic congestion. It is, therefore, vital to understand the impact of reduced transit use on the overall efficiency of the transportation roadway system, particularly in dense urban areas. This project attempted to forecast the congestion post-pandemic using large-scale traffic and transit data. The findings of this research can be valuable for policymakers, urban planners, and transportation agencies in understanding the effects of the pandemic on transportation systems and making informed decisions.

Chapter 3. Data Collection

The data for this study was taken from multiple sources. The transit ridership data was downloaded from the National Transit Database (NTD) for 2019 to 2022. A private company dataset of traffic speeds called INRIX is used to calculate congestion metrics. Throughout the year, INRIX publishes average traffic speeds for each road section in 15-minute intervals based on a typical week. When evaluating trip delays, reference speeds from the INRIX dataset are employed as a benchmark because they are low-volume conditions. High-quality congestion measurements are derived by merging the INRIX speed data with volume and roadway inventory data from FHWA's HPMS files, providing an accurate analysis of travel delay numbers. Detailed methodology for estimating the performance measures is given in the Urban Mobility Report (UMR),2021 (Schrank et al., 2021)

Chapter 4. General Trends in Transit Ridership across USA

Figure 6 shows the change in the average daily ridership of public transit in the USA over the course of 6 years. When comparing 2019 to 2020, the impact of COVID on P.T. ridership is evident, with a more than 50% drop in trips in 2020.

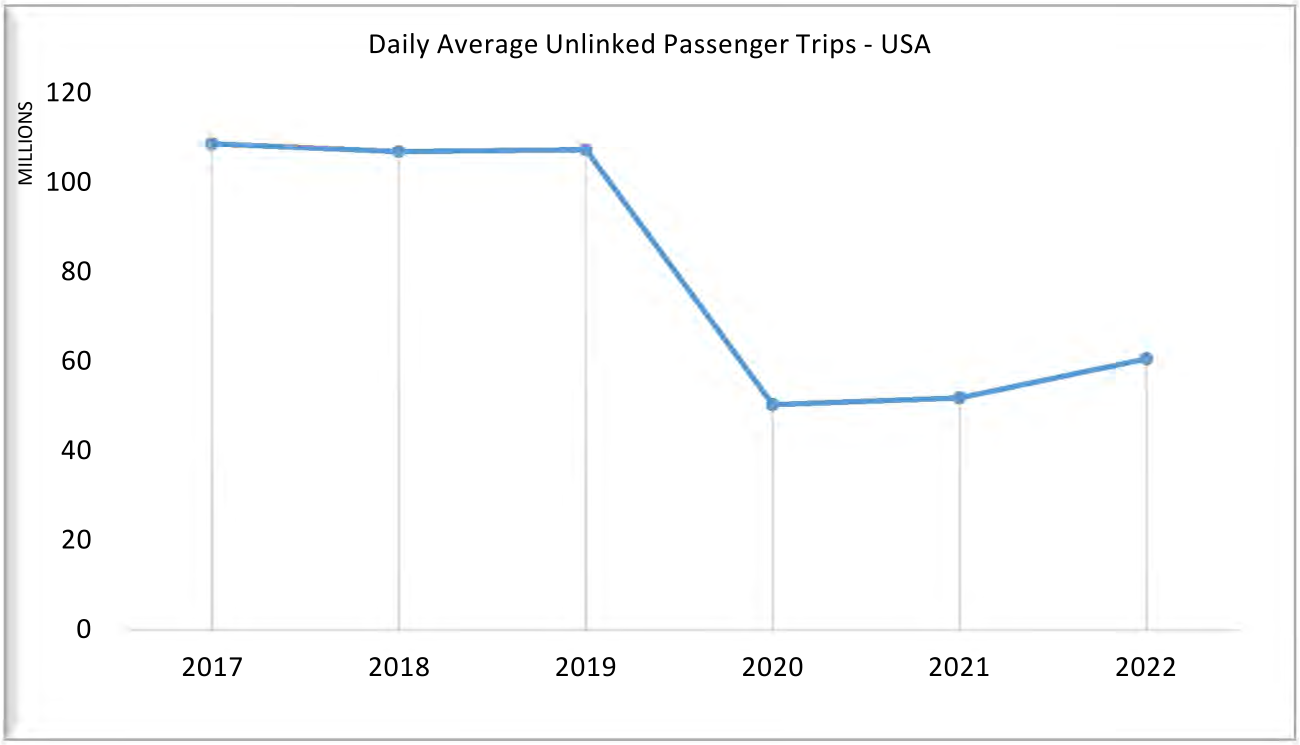

Figure 6. Transit Ridership Trends in the USA from 2017 to 2022

Breaking it down by months (Figure 7), the ridership is seen declining from March 2020 until it reaches its minimum in March 2021. This was due to almost 30 million COVID cases in the United States during the month of March 2021. Even though ridership began to increase after May 2021, it has yet to fully recover and is around 37% lower than in 2019.

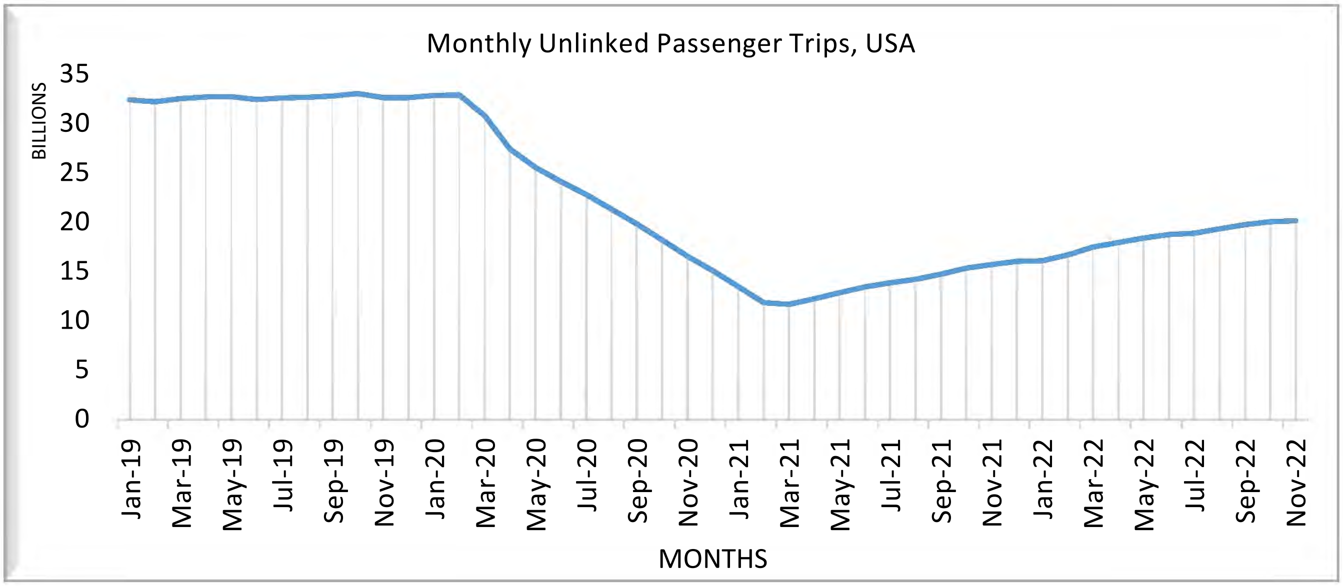

Figure 7. Monthly Ridership from 2019 to 2022

Figure 8 demonstrates the changes in ridership for different public transit modes before and after the COVID-19 pandemic. Overall, the transit ridership experienced a steep decline in March 2020 and then started to increase gradually. However, as of November 2022, the ridership for all modes of transit remained 50 to 100 million below the pre-COVID levels.

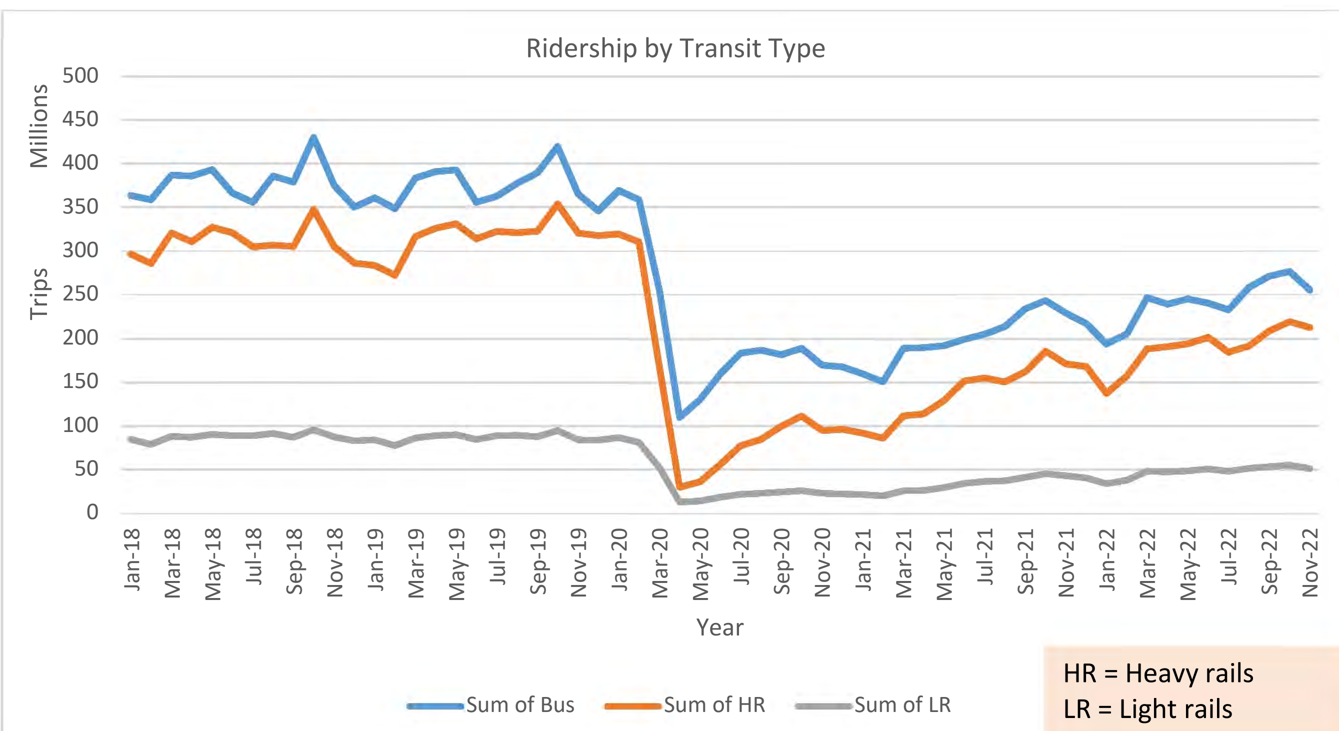

Figure 8. Monthly Ridership by Modes from 2019 to 2022

4.1 Passenger Miles Travelled – Methodology

To evaluate the change in travel behavior post-COVID, the research team analyzed transit data from 2019 to 2022. This was done by first downloading the data from the National Transit Database (NTD). The datasets contain information on ten modes of transportation. The research team divided these ten modes into four categories (see Table 1): bus (M.B.), heavy rail (H.R.), light rail (L.R.), and monorail (M.R.). For instance, buses, commuter buses, and bus rapid transit were combined into one category under Bus (M.B.). Commuter rail is included under the light rail category because Commuter rail and light rail systems often share operational characteristics and service patterns. In some cases, commuter rail and light rail lines may share tracks or have interconnectivity at certain points. This can occur, for instance, when commuter rail lines utilize portions of existing light rail networks or when light rail lines extend their routes to serve suburban areas traditionally covered by commuter rail.

Table 1. Categorization of Different Modes of Transportation

Categories	MODES			
Bus (M.B.)	Bus (M.B.)	Commuter Bus (C.B.)	Bus Rapid Transit (R.B.)	
Heavy rail (H.R.)	H.R.			
Light rail (L.R.)	Commuter rail (C.R.)	Light rail (L.R.)	Hybrid rail (Y.R.)	Streetcar rail (S.R.)
Monorail (M.R.)	Monorail (M.R.)	Automated Guideway (A.G.)		

Once the modes were categorized, the research team estimated daily passenger miles traveled (PMT) from the NTD dataset. It contains information on the total number of unlinked trips made per year by each agency in a specific metropolitan area. It also includes information on the average length of each agency's trips that year. The research team used this information to calculate the average trip length by each transit type and metro. This weighted average trip length was then multiplied by the total number of unlinked trips made on each type of transit to estimate the annual passenger miles traveled (PMT) for each metro. The annual PMT was divided by 365 to get the Daily-PMT. Table 2 provides an example of the annual PMT and daily PMT for Los Angeles-Long Beach-Anaheim, CA, in 2022.

Table 2. Calculation of Passenger Miles Traveled in Los Angeles–Long Beach–Anaheim, CA (2022)

Name	Unlinked Passenger Trips (UPT)	Weighted Average Trip length (L) (miles)	Annual PMT 2022 (UPT*L) (person-miles)	Daily-PMT-2022 (UPT*L)/365
Heavy rail	25,767,716	5	135,136,210	370,236
Light rail	36,170,808	9	338,296,861	926,841
BUS	292,546,639	3	933,855,569	2,558,508
Total	354,485,163		1,407,288,638	3,855,585

All the metros were arranged in decreasing order of their Daily PMT, and the top 19 metros, in addition to Austin and Bryan-College Station, were selected for further analysis. These 19 metros were categorized into very large, large, and medium-sized based on their population. However, it is important to note that since only 18 metros were considered in this study, the categorization of metros differs from that of the Urban Mobility Report (UMR). Metros with a population of more than 8 million were classified as very large, metros with a population between 3 and 6 million were classified as large, and metros with a population of less than 3 million were classified as medium-sized.

Table 3. Top 19 Selected Metropolitan Areas

Metro	2019 Population	2022 Population	Percentage Increase	Daily PMT 2019 (000)	Classification
Atlanta, GA	5,862,424	6,094,752	4%	4450	Large
Baltimore, MD	2,796,733	2,840,005	2%	2767	Medium
Boston, MA	4,832,346	4,912,449	2%	1422	Large
Chicago, IL	9,508,605	9,566,955	1%	7485	Very Large
Denver, CO	2,892,066	2,959,386	2%	1894	Medium
Hartford, CT	1,207,677	1,215,703	1%	1057	Medium
Los Angeles, CA	13,249,614	13,111,917	-1%	9922	Very Large
Miami, FL	6,090,660	6,123,949	1%	1669	Large
Minneapolis, MN	3,573,609	3,678,328	3%	1905	Medium
New York, NY	19,294,236	19,908,595	3%	65762	Very Large
Philadelphia, PA	6,079,130	6,232,894	3%	4253	Large
Pittsburgh, PA	2,331,447	2,365,501	1%	1428	Medium
Portland, OR	2,445,761	2,505,312	2%	5832	Medium
Salt Lake City, UT	1,201,043	1,254,675	4%	740	Medium
San Diego, CA	3,316,073	3,289,701	-1%	304	Medium
San Francisco, CA	4,701,332	4,692,242	0%	793	Large
San Jose, CA	1,987,846	1,981,584	0%	523	Medium
Seattle, WA	3,871,323	4,001,701	3%	5452	Large
Washington, DC	6,196,585	6,346,083	2%	1280	Large

4.2 Travel Delay

After selecting the 18 metros for more detailed analysis, the research team attempted to assess the impact of reduced transit usage (as we saw in section 4.1) on the overall performance of the freeways. With fewer people using public transit systems, there might be an increased reliance on private vehicles. This leads to more cars on the road, which can result in additional congestion and traffic delays. The additional vehicles put strain on the existing infrastructure, including freeways, leading to reduced efficiency and increased travel times.

Delay is a fundamental metric for estimating and quantifying congestion in transportation systems. Delay is the extra time that travelers spend on their journeys when compared to the travel time they would experience under free-flow conditions when there is no congestion. Longer delay times indicate a higher level of congestion, which can cause frustration, stress, and decreased productivity for travelers. Furthermore, traffic congestion may increase fuel consumption, pollution, and total transportation expenses, which affects both individuals and businesses. Measuring delay allows transportation planners and regulators to identify congestion hotspots, prioritize infrastructure expenditures, and apply effective mitigation techniques to improve transportation system efficiency and sustainability. Estimated delays can aid in decision-making and the creation of transportation policies and initiatives aimed at reducing congestion and improving the overall travel experience for all travelers.

The research team used data on vehicular delay for the top 18 metros from the Urban Mobility Report. Table 4 displays data on the total annual vehicle delay measured in thousand hours for 2019, 2020, 2021, and 2022, as well as the percent change from the previous year. Interestingly, when comparing with 2019 levels, some urban areas still experienced a significant reduction in delay person-hours, while others have either reached the 2019 levels or even exceeded them. Salt Lake City experienced an increase of 7% in total annual delay from 2019 to 2022, reaching 31,614 hours. Los Angeles, CA, had a 5% increase, with a total annual delay of 995,556 hours in 2022. The table is missing information on Minneapolis, Portland, and Seattle, as the research team was not able to get information on these metros at the time of the analysis.

Overall, the data suggests that congestion levels in many U.S. metros are gradually approaching or exceeding the pre-pandemic levels, indicating a potential challenge for policymakers and urban planners to address the growing transportation demands while reducing the negative impacts of congestion.

Table 4. Total Annual Delay (1000 hours)

Metropolitan Area	**Total Annual Delay (1000 Hours)**				**Percent change from 2019**
	2019	2020	2021	2022	2019-2022
Salt Lake City	29,571	17,124	27,973	31,614	7%
Los Angeles CA	952,183	365,543	777,389	995,556	5%
Miami FL	309,019	112,879	243,526	315,984	2%
Philadelphia PA	172,804	100,726	166,027	176,742	2%
Atlanta GA	230,899	109,475	190,813	232,272	1%
Denver-Aurora CO	111,366	46,181	93,749	110,908	0%
Pittsburgh PA	44,556	24,743	39,001	43,830	-2%
San Diego CA	145,568	55,433	114,993	142,070	-2%
San Francisco CA	255,724	112,507	208,561	248,889	-3%
Hartford CT	28,583	16,928	20,702	27,475	-4%
Chicago IL-IN	331,657	172,876	271,088	306,001	-8%
New York NY	846,704	494,268	654,315	781,553	-8%
Austin TX	81,069	48,435	60,001	74,022	-9%
San Jose CA	118,687	46,377	68,269	100,700	-15%
Baltimore MD	102,994	44,292	67,052	83,763	-19%
Boston MA-NH-RI	209,231	122,348	138,524	165,890	-21%
Washington DC	256,476	101,775	136,630	188,563	-26%
Minneapolis MN	110,297	59,835			
Portland OR-WA	78,309	36,065			
Seattle WA	168,998	69,016			

The Travel Time Index (TTI) is another measure of congestion. The TTI measures the ratio of travel time in peak traffic periods compared to free-flow travel time, with higher values indicating greater congestion. An escalation in TTI values indicates that motorists face extended travel durations during peak periods, leading to a multitude of negative consequences. These include increased fuel usage, increased greenhouse gas emissions, and a downturn in economic efficiency as a result of time wasted. Moreover, such delays in travel can also exert a significant psychological toll on drivers as they grapple with the stress associated with travel disruptions, delays, and unpredictability. This travel-related stress can negatively influence individuals' overall well-being, decision-making capabilities, and productivity, underscoring the importance of addressing traffic congestion to improve not only the environmental and economic aspects of urban living but also the mental health of those navigating these congested spaces. In this study, we used the consumer stress index (CSI) to reflect the psychological stress experienced by consumers due to traffic congestion. The Consumer Stress Index (CSI) is a measure used to assess the level of congestion and travel stress experienced by commuters during peak travel periods. It takes into account the travel speed from the direction with the most congestion in each peak period to reflect the conditions faced by commuters traveling in the predominant directions.

Table 5 presents fluctuations in both TTI and CSI. For instance, Los Angeles-Long Beach-Anaheim, CA experienced a significant drop in TTI from 1.52 in 2019 to 1.16 in 2020, followed by an increase to 1.34 in 2021 and 1.5 in 2022. The CSI values for this urban area also followed a parallel trend, decreasing from 1.76 in 2019 to 1.21 in 2020 and then increasing to 1.37 in 2021 and 1.55 in 2022.

Table 5. Travel Time Index and Consumer Stress Index

	TRAVEL TIME INDEX				CONSUMER STRESS INDEX			
Urbanized Area	2019	2020	2021	2022	2019	2020	2021	2022
Atlanta GA	1.3	1.1	1.17	1.25	1.4	1.11	1.22	1.34
Austin TX	1.35	1.13	1.21	1.3	1.51	1.14	1.24	1.33
Baltimore MD	1.26	1.07	1.11	1.19	1.32	1.09	1.14	1.25
Boston MA	1.28	1.12	1.16	1.22	1.31	1.13	1.17	1.24
Chicago IL-IN	1.29	1.1	1.23	1.3	1.32	1.11	1.24	1.35
Denver CO	1.32	1.09	1.21	1.28	1.37	1.1	1.25	1.34
Hartford CT	1.17	1.07	1.12	1.15	1.18	1.09	1.14	1.16
Los Angele CA	1.52	1.16	1.34	1.5	1.76	1.21	1.37	1.55
Miami FL	1.34	1.11	1.23	1.34	1.46	1.12	1.27	1.44
Minneapolis MN	1.26	1.11			1.28	1.12		
New York NY	1.36	1.17	1.23	1.32	1.39	1.21	1.27	1.37
Philadelphia PA	1.24	1.12	1.17	1.23	1.27	1.13	1.18	1.25
Pittsburgh PA	1.18	1.08	1.12	1.16	1.19	1.09	1.16	1.21
Portland OR	1.35	1.1			1.45	1.11		
Salt Lake City UT	1.17	1.06	1.14	1.18	1.19	1.07	1.16	1.19
San Diego CA	1.34	1.1	1.16	1.29	1.39	1.11	1.18	1.33
San Francisco CA	1.51	1.16	1.32	1.48	1.65	1.18	1.41	1.5
San Jose CA	1.44	1.12	1.2	1.35	1.55	1.12	1.21	1.39
Seattle WA	1.37	1.11			1.43	1.12		
Washington DC	1.36	1.12	1.14	1.25	1.44	1.14	1.19	1.34

The results from Table 5 indicate that the relationship between TTI and CSI is consistent across various metros, with higher TTI values corresponding to higher CSI values. It is evident that traffic congestion has a significant impact on consumers' stress levels, and as traffic conditions returned to pre-pandemic levels in 2021 and 2022, the stress experienced by consumers also increased.

The graph below, from the 2021 Urban Mobility Report (Schrank et al., 2021), compares the percentage of delay for each hour of the day for 2019 and 2020. This graph shows that while the share of delay for the AM and PM peak periods was reduced in 2020, the AM peak almost disappeared. In addition, increased flexibility in work schedules and remote work allowed people to avoid traveling during peak times, so mid-day had a higher share of overall delay in 2020. Anecdotal accounts and some additional analyses since the release of the 2021 Urban Mobility Report have shown that the PM peak has returned approximately to pre-pandemic levels, the AM Peak is still below 2019 levels, and there is more congestion between the morning and evening peak periods (Figure 9).

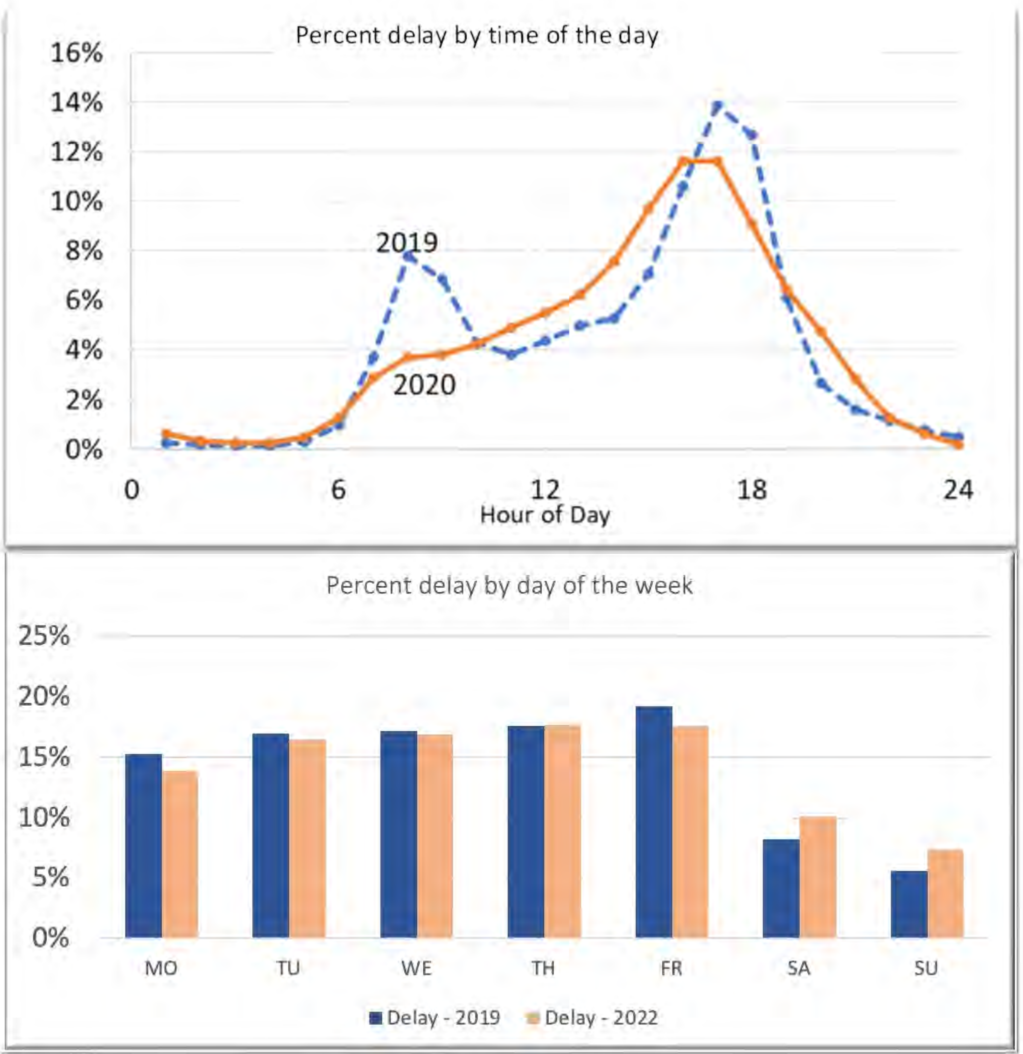

Figure 9. Percent Delay Across the Time of Day and Day of Week

Traffic patterns by day of the week have changed since 2019, with Monday delays having a lower percentage share of the overall delay and a greater percentage of delays occurring on the weekends than before the pandemic. This is likely due to hybrid work schedules providing commuters flexibility on days to commute and more commuting occurring in the middle of the week.

4.3 Fuel Consumption Due to Congestion

Fuel consumption due to congestion is a growing concern in urban areas as traffic congestion not only causes delay and frustration but also leads to increased fuel consumption and environmental pollution. Excessive idling, stop-and-go traffic, and inefficient driving patterns contribute to wasted fuel and elevated greenhouse gas emissions. This problem is exacerbated in densely populated metropolitan areas with high levels of vehicle ownership and inadequate public transportation infrastructure. Table 6 shows the annual excess fuel consumed (in thousands) and excess fuel consumed per commuter. The data in this table was also obtained as a part of the UMR effort.

Table 6. Excess Fuel Consumption Due to Congestion (in Gallons)

Annual Excess Fuel Consumed (000)					Excess Fuel Consumed per 2019 Commuter			
UZA	**2019**	**2020**	**2021**	**2022**	**2019**	**2020**	**2021**	**2022**
Chicago IL-IN	136,878	71,348	71,348	115,383	30	16	27	29
Los Angeles CA	345,453	132,619	132,619	282,440	35	14	32	39
New York NY	335,880	196,072	196,072	250,539	39	23	31	36
Philadelphia PA	69,310	40,400	40,400	67,982	26	15	28	28
Seattle WA	67,508	27,569	27,569		32	13		
Miami FL	120,912	44,167	44,167	91,788	37	13	30	37
Atlanta GA	121,952	57,820	57,820	67,453	31	15	19	21
Washington DC	98,110	38,932	38,932	51,389	41	16	25	31
Baltimore MD	39,125	16,825	16,825	25,476	23	10	16	19
Portland OR	35,070	16,151	16,151		31	14		
Salt Lake City UT	14,916	8,638	8,638	13,572	24	14	24	25
San Diego CA	34,240	13,039	13,039	38,801	24	9	30	35
Denver CO	44,960	18,644	18,644	37,424	25	10	23	25
Hartford CT	12,053	7,138	7,138	9,147	22	13	18	23
Minneapolis MN	40,837	22,154	22,154		22	12		
San Diego CA	34,240	13,039	13,039	38,801	24	9	30	35
San Jose CA	41,655	16,277	16,277	25,296	32	13	24	31
Pittsburgh PA	19,340	10,740	10,740	16,989	21	12	20	21

In 2022, Los Angeles-Long Beach-Anaheim, CA, had the highest annual excess fuel consumption at 282,440 (000), followed by New York-Newark, NY-NJ-CT at 250,539 (000). These two metros also had the highest excess fuel consumed per 2019 commuter, with 39 and 36 gallons, respectively.

4.4 Work-from-Home

The widespread adoption of remote work or work-from-home policies during the COVID-19 pandemic has had a significant impact on transit ridership. With fewer people commuting to traditional workplaces, transit agencies have seen a decline in ridership, particularly during peak hours. Figure 10 shows that there has been a significant increase in the number of people working from home in all 18 metropolitan areas. For instance, about 6% of employees worked from home in San Francisco in 2019, which increased to 16% in 2021, according to the U.S. Census.

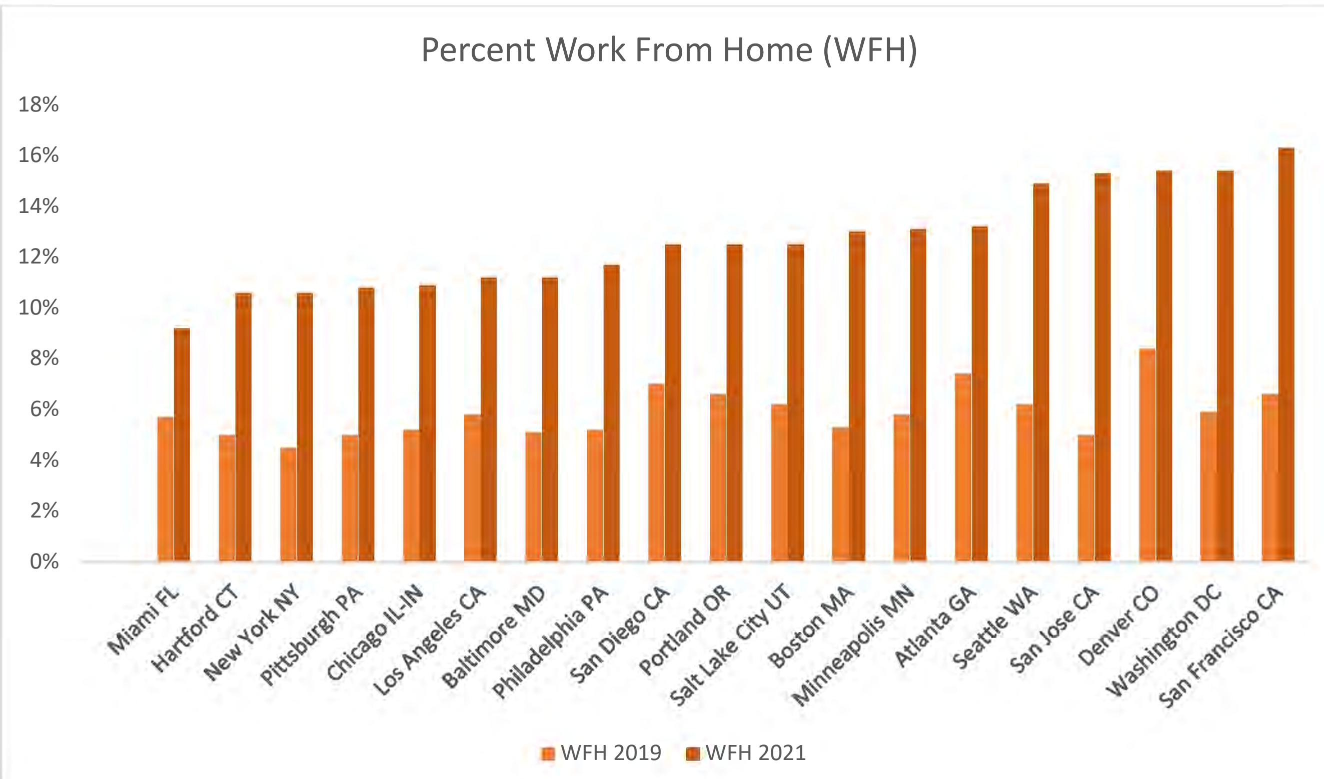

Figure 10. Work from Home (WFH) Trends (Source: U.S. Census 2021 and 2019)

Table 7 provides information on three important metrics for urban transportation in the 18 metropolitan areas. The first column shows the geometric mean growth rate of working from home from 2019 to 2022, which is an indicator of how much the COVID-19 pandemic has affected the way people work in each city. The geometric growth rate is a valuable tool in situations where the growth or decline of a variable is not linear but follows a compounding or exponential pattern. It provides a more comprehensive understanding of growth dynamics over time and helps in making informed decisions and predictions. The table indicates that metros such as San Jose, CA, and Washington DC-VA-MD have experienced the greatest increase in work-from-home arrangements with growth rates of 167% and 134%, respectively.

The second column displays the number of vehicles per household in 2020. The number of vehicles per household is an important metric that reflects the level of car dependence in a particular area. Table 7 indicates that Salt Lake City-West Valley City, UT, has the highest number of vehicles per household, with a value of 2.04, while the New York-Newark, NY-NJ-CT metropolitan area has the lowest value, with 1.24 vehicles per household.

The third column displays the percentage of households with access to a vehicle in 2020. This metric reflects the level of car ownership in a particular area. The table indicates that metros such as Salt Lake City-West Valley City, UT, and San Jose, CA, have the highest percentage of households with access to a vehicle, with values of 95% and 95%, respectively. Meanwhile, the New York-Newark, NY-NJ-CT metropolitan area has the lowest value, with only 69% of households having access to a vehicle.

Table 7. Work from Home and Vehicle Ownership (Source: Timmons, 2023)

Name	Work from home geometric mean growth rate from 2019 to 2021	Vehicles per household (2020)	Percent of households with access to a vehicle (2020)
Philadelphia, PA	103%	1.65	88%
Seattle, WA	119%	1.87	92%
Miami, FL	57%	1.66	92%
Atlanta, GA	68%	1.89	94%
San Francisco, CA	120%	1.75	88%
Boston, MA	122%	1.62	87%
Washington, DC	134%	1.78	90%
Salt Lake City, UT	88%	2.04	95%
Portland, OR	101%	1.86	92%
San Diego, CA	67%	1.96	95%
Baltimore, MD	106%	1.75	90%
Denver	76%	1.94	95%
Minneapolis, MN	106%	1.86	93%
San Jose, CA	167%	2.04	95%
Hartford, CT	95%	1.78	91%
Pittsburgh, PA	98%	1.67	89%
New York, NY	116%	1.24	69%
Los Angeles, CA	79%	1.89	92%
Chicago	93%	1.65	88%

4.5 Travel Behavior Trends across Different Modes

This report now delves into an in-depth analysis of mode-wise transit usage changes in metropolitan areas of various sizes, including very large, large, and medium-sized metros. By examining the trends across different modes of transportation, this report seeks to provide valuable insights into the evolving travel behavior patterns in these urban areas.

4.5.1 Very Large Metros

Figure 11 shows the transit mode share for the very large metros, New York, Los Angeles, and Chicago. As can be seen, heavy rail is the primary Transit mode in New York, accounting for roughly half of all daily Transit travel. In the case of New York, the extensive and well-established subway system, comprising a vast network of heavy rail lines, has been developed and expanded over many decades. This efficient and comprehensive subway system serves as the backbone of New York's transit infrastructure, enabling a large portion of the population to rely on heavy rail for their daily commuting needs.

Chicago's transit mode share distribution reflects a more balanced utilization of heavy rail and extensive commuter rail. The city benefits from an extensive transit network, including the iconic "L" system, which combines elevated heavy rail lines and underground subways. The availability of such transit options offers commuters flexibility and accessibility, contributing to their relatively equal transit mode shares.

As opposed to New York and Chicago, Los Angeles had 62% bus mode share and only 10% heavy rail mode share. Historically, the city has faced challenges in developing a comprehensive heavy rail system due to geographical constraints, such as a dispersed population and a vast suburban area. While Los Angeles has made significant investments in expanding its heavy rail network in recent years, the extensive bus network remains a crucial mode of transportation for residents.

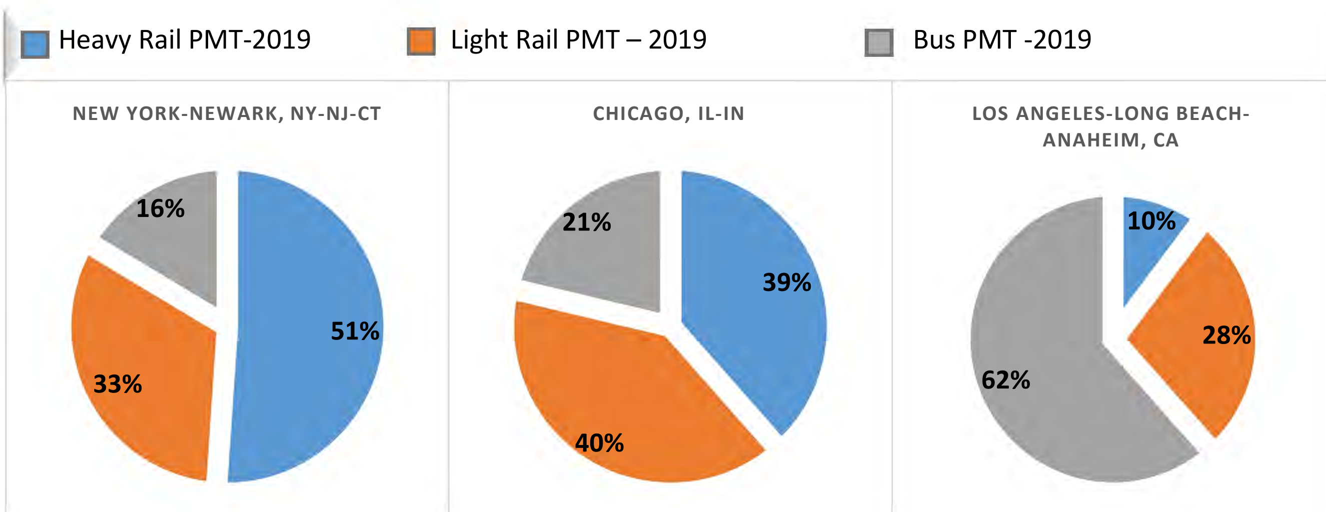

Figure 11. Transit Mode Share of Top 3 Metros with Highest Population

Although recovering, the number of public transit riders still has not reached 2019. Figure 12 shows the change in daily passenger miles traveled (PMT) in New York from 2019 to 2022. New York has the highest public transit ridership in the country, with more than 4 billion daily trips in 2019. Ridership of heavy rail in New York dropped by 59% in 2020 and was down by 35% in 2022.

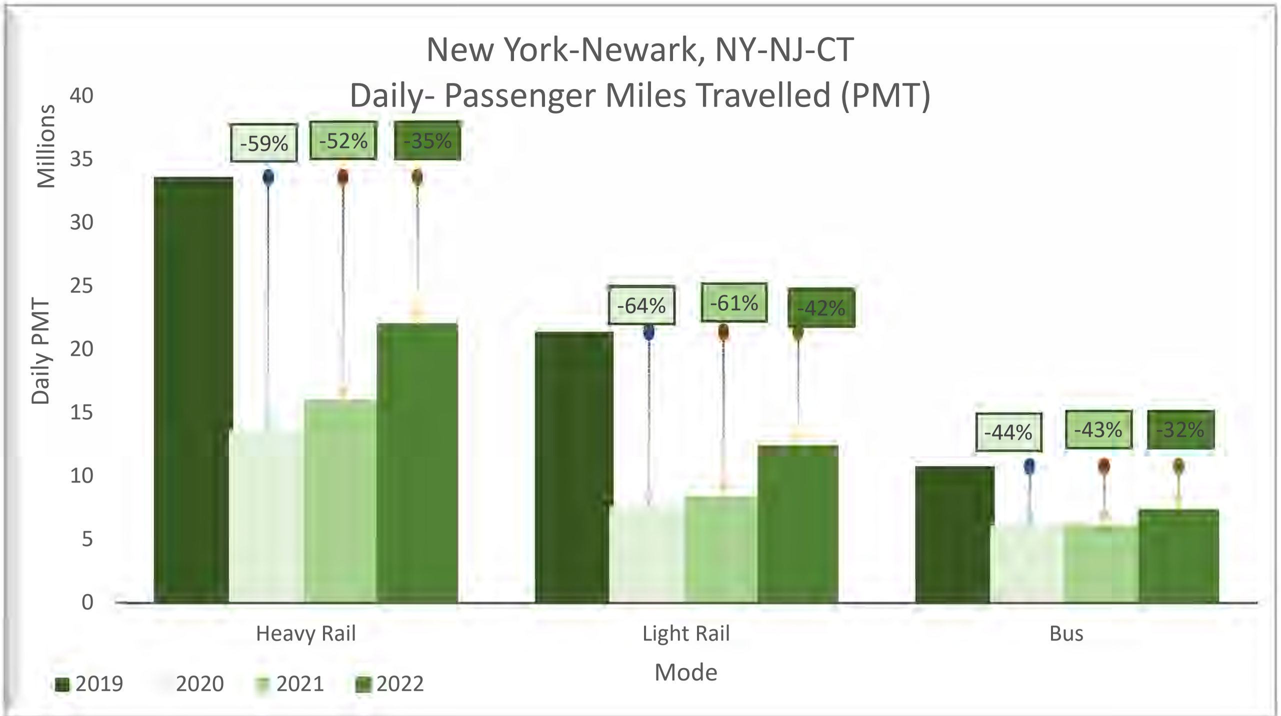

Figure 12. Change in Daily Passenger Miles Travelled (PMT) in New York from 2019 to 2022

Table 8 presents changes in public transit ridership for different modes of transportation in metropolitan areas of very large size from 2019 to 2022. In the New York metro, heavy rail has hit the lowest, with a decline of 35% in 2022, followed by light rail (-42%) and bus (-32%). In Chicago, heavy rail has experienced the largest decline in ridership (-53%), followed by light rail (-61%) and bus (-42%). In Los Angeles-Long Beach-Anaheim, heavy rail (-38%) and bus (-29%) have been affected less than light rail (-44%). These numbers indicate that heavy rail and bus were more resilient to the pandemic than light rail.

Table 8. Public Transit Ridership Change in Very Large-Sized Metros (2019–2022)

Urbanized Area	Mode	Ridership change (2019-2022)		
		2019-2020	2019-2021	2019-2022
New York-Newark, NY-NJ-CT	Heavy Rail	-59%	-52%	-35%
	Light Rail	-64%	-61%	-42%
	Bus	-44%	-43%	-32%
Chicago	Heavy Rail	-65%	-64%	-53%
	Light Rail	-73%	-77%	-61%
	Bus	-49%	-51%	-42%
Los Angeles–Long Beach–Anaheim, CA	Heavy Rail	-45%	-49%	-38%
	Light Rail	-48%	-54%	-44%
	Bus	-43%	-38%	-29%

In general, transit has seen a much greater decline in ridership than personal vehicle usage. Table 9 shows a decrease in vehicle miles traveled (VMT) is less than 10% in 2022 compared to 2019. During that same time, transit PMT has decreased by more than 30%.

Table 9. Vehicle Miles Travelled – Very Large-Sized Metros

	Change in VMT as %		
Metros	2019-2020	2019-2021	2019-2022
Chicago IL-IN	-20%	-9%	-6%
Los Angeles–Long Beach–Anaheim CA	-20%	-11%	-9%
New York-Newark NY-NJ-CT	-26%	-12%	-9%

Table 10 shows that Los Angeles witnessed a 5% increase in total annual delay in 2022 compared to 2019, whereas total annual delay in New York and Chicago decreased by 8%.

Table 10. Total Delay – Very Large Metros

	Total Annual Delay (1000 Hours)				**Percent change from 2019**
	2019	2020	2021	2022	2019-2022
New York NY	846,704	494,268	654,315	781,553	-8%
Chicago IL-IN	331,657	172,876	271,088	306,001	-8%
Los Angeles CA	952,183	365,543	777,389	995,556	5%

The availability of remote work options in different sectors can influence transit ridership and personal car use. Figure 10 (see above) shows that the percentage of work from home in New York, Los Angeles, and Chicago increased from 4% to 10% between 2019 and 2022. The research team looked at the employment distribution across different sectors (Figure 13) to determine the potential to work from home for each metro area. The data is categorized into four broad sectors: Farming, Construction, Retail; Arts, Utilities, Health, and Manufacturing; Wholesale, Government, Real Estate; and Education, Technical, and Management. Among the four sectors, Wholesale, Government, Real Estate, and Education, Technical Management have more potential to work from home than the other sectors. In New York, the potential work-from-home would be 38% (15% + 23%) of the total employment, Chicago would be around 35%, and Los Angeles is approximately 31%. The potential to work from home in very large areas is likely greater than the current approximately 10% that were working from home in 2021. This could have an impact on public transit ridership and the time of day that people travel.

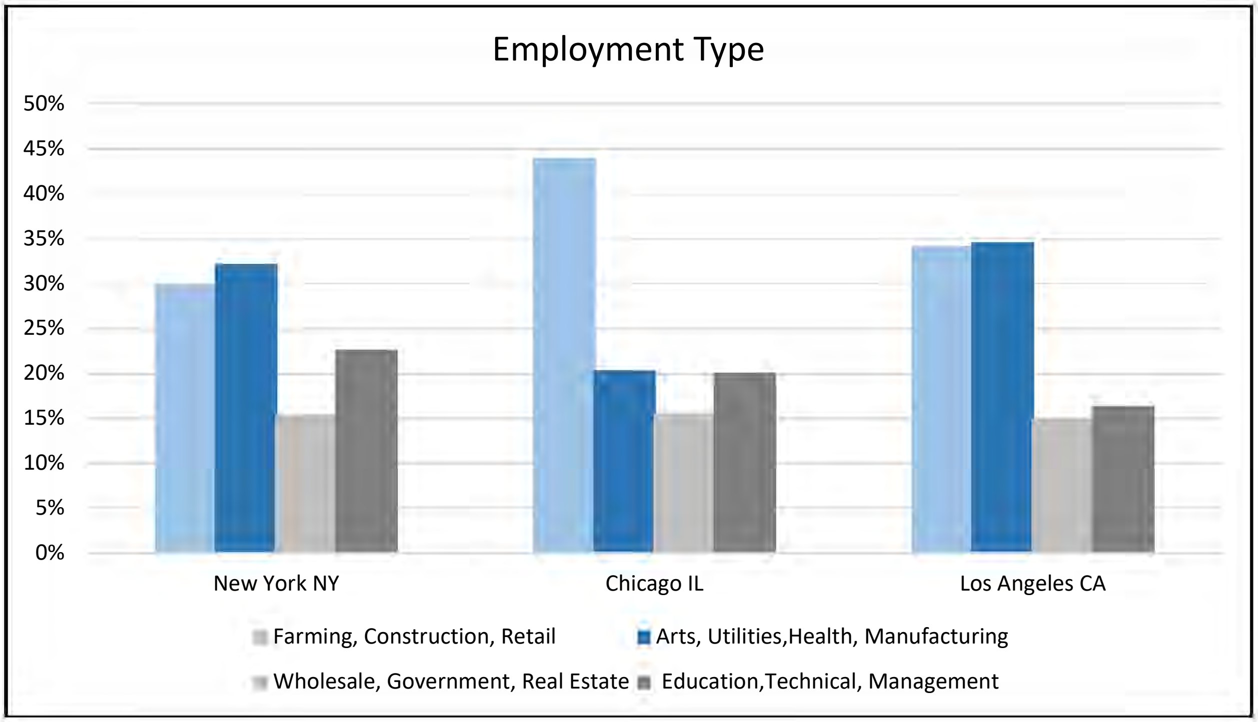

Figure 13. Employment Distribution of Very Large Metros

The very large metro areas have seen a decrease of more than 30% in public transit ridership, while the VMT has decreased by less than 10% between 2019 and 2022. The delay in Los Angeles is now 5% higher than it was in 2019, which may be caused by changes in the time of day people travel, reduced public transit use, and increased auto use as VMT and auto delay continue to rise.

Compared to metros like New York or Chicago, Los Angeles has a relatively higher transit mode share of buses but lower shares of heavy rail and light rail. Household auto ownership is 92 percent in Los Angeles compared to 69 percent in New York, which implies that commuting and travel in Los Angeles is more reliant on the automobile than travel in New York. The lack of an extensive rail network in Los Angeles means that many commuters must rely on buses or cars for their daily transportation needs. While light rail does have a 28% mode share, it may not cover as many areas or offer the same level of convenience as comprehensive subway systems, leading to a limited impact on reducing congestion and delays.

As mentioned previously, increased flexibility in work schedules and remote work has allowed people to avoid traveling during the traditional peak times, so mid-day delays have increased. Although delay has not reached the 2019 levels in New York or Chicago by 2022, it has continued to rise for similar reasons. Moving forward, the very large metro areas need to monitor work-from-home trends, along with public transit ridership trends, to help anticipate long-term transportation changes that result in changing travel needs.

4.5.2 Large Metros

Moving on to large metros with a population of more than 3 million, Figure 14 shows the transit mode share of large-sized metros. In 2019, Washington DC, San Francisco, and Atlanta had the highest heavy rail mode share, followed by buses. In Seattle and Miami, buses have a major share of the transit market. The mode share for all three transit types is almost equal in Philadelphia.

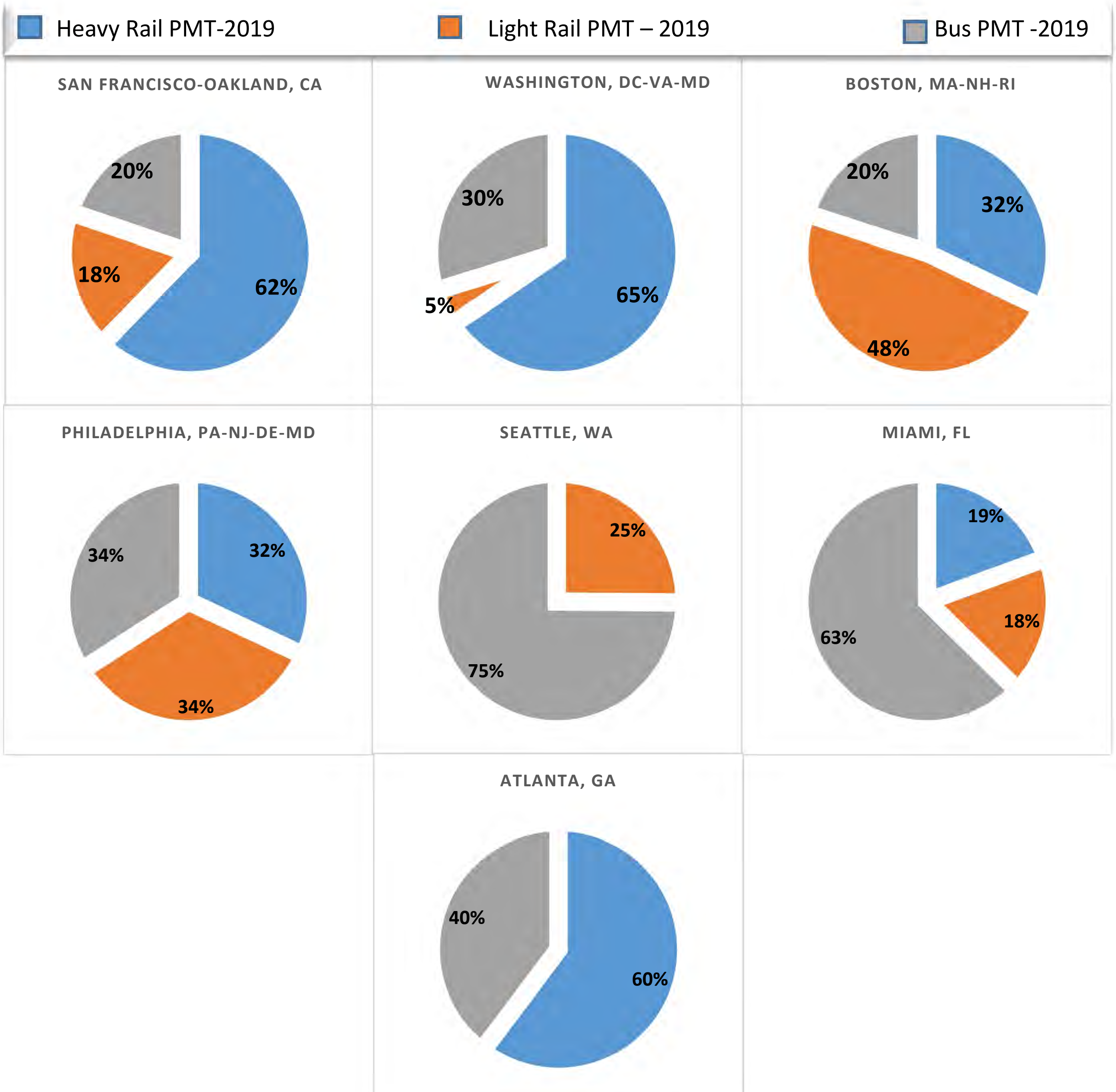

Figure 14. Share of Transit Types by PMT in Large Metros

Table 11 shows the ridership changes for different modes of public transportation in some of the large-sized metros between the years 2019 and 2022. The ridership changes are expressed as percentages relative to the 2019 ridership levels. The data shows that the COVID-19 pandemic has had a significant impact on ridership across all types of transit, with heavy rail and light rail experiencing around 50% decline in ridership. Although the overall ridership in most metros remains significantly below pre-pandemic levels, Seattle and Miami have experienced a slight rebound in ridership for certain modes of transportation. For instance, the light rail ridership in Seattle has gone from a 68% reduction in 2020 to

18% lower in 2022, and bus ridership in Miami is 20% lower than respective 2019 levels. In Philadelphia and Washington DC, bus ridership is rebounding faster than in other modes, but it still remains over 30% lower than in 2019.

Table 11. Public Transit Ridership Change in Large-Sized Metros (2019–2022)

Name	Mode	Ridership change (2019-2022)		
		2019-2020	2019-2021	2019-2022
Philadelphia, PA	Heavy Rail	-58%	-62%	-49%
	Light Rail	-64%	-68%	-53%
	Bus	-51%	-54%	-35%
Seattle, WA	Heavy Rail	-	-	-
	Light Rail	-68%	-58%	-18%
	Bus	-53%	-60%	-49%
Miami, FL	Heavy Rail	-47%	-46%	-34%
	Light Rail	-51%	-43%	-31%
	Bus	-37%	-30%	-20%
Atlanta, GA	Heavy Rail	-61%	-63%	-54%
	Light Rail	-65%	-62%	-48%
	Bus	-38%	-49%	-48%
Washington, DC	Heavy Rail	-71%	-76%	-61%
	Light Rail	-73%	-85%	-74%
	Bus	-53%	-47%	-32%
San Francisco, CA	Heavy Rail	-73%	-79%	-65%
	Light Rail	-75%	-83%	-67%
	Bus	-50%	-55%	-40%

Figure 15 shows the ridership change in Boston. Despite light rail having the highest mode share, it still experienced a 45% decrease in ridership in 2022 compared to 2019, indicating a significant decline in usage of this mode of transportation.

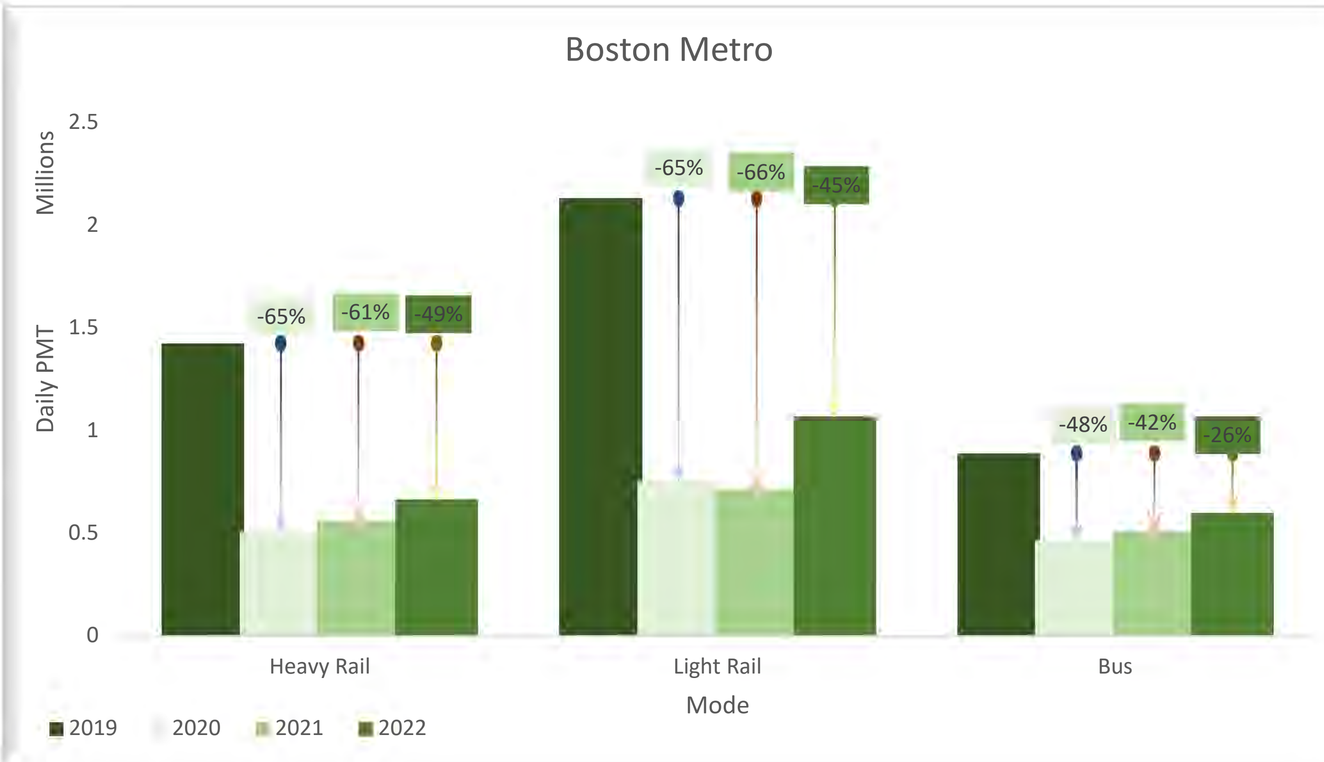

Figure 15. Public Transit Ridership Change in Boston (2019–2022)

In general, transit has seen a much greater decline in ridership than personal vehicle usage. Table 12 shows that the VMT is increasing in Philadelphia and that there is less than a 10% reduction in the other large metro areas. During that same time, overall transit use has decreased by more than 30%.

Table 12. Vehicle Miles Travelled – Large-Sized Metros

Metros	2019-2020	2019-2021	2019-2022
Philadelphia PA	-23%	-1%	1%
Seattle WA	-22%		
Miami FL	-19%	-7%	-4%
Atlanta GA	-13%	-10%	-7%
Washington DC	-23%	-10%	-9%
San Francisco, CA	-28%	-14%	-12%
Boston	-24%		

Table 13 shows that Philadelphia, Miami, and Atlanta experienced a small increase in annual delay, whereas the delay in Washington, DC, was 26% lower compared to 2019.

Table 13. Total Annual Delay – Large Metros

Metros	Total Annual Delay (1000 Hours)				Percent change from 2019
	2019	2020	2021	2022	2019-2022
Atlanta GA	230,899	109,475	190,813	232,272	1%
Philadelphia PA	172,804	100,726	166,027	176,742	2%
Miami FL	309,019	112,879	243,526	315,984	2%
San Francisco CA	255,724	112,507	208,561	248,889	-3%
Washington DC	256,476	101,775	136,630	188,563	-26%
Seattle WA	168,998	69,016			

Atlanta and Washington, DC, have the highest potential work from home, accounting for 53% and 43% of the total employment, whereas Philadelphia and Miami are expected to have the most work trips (Figure 16). This could be one of the reasons why there is more than a 50% drop in transit use in Washington, D.C., Atlanta, and Tech hubs in San Francisco.

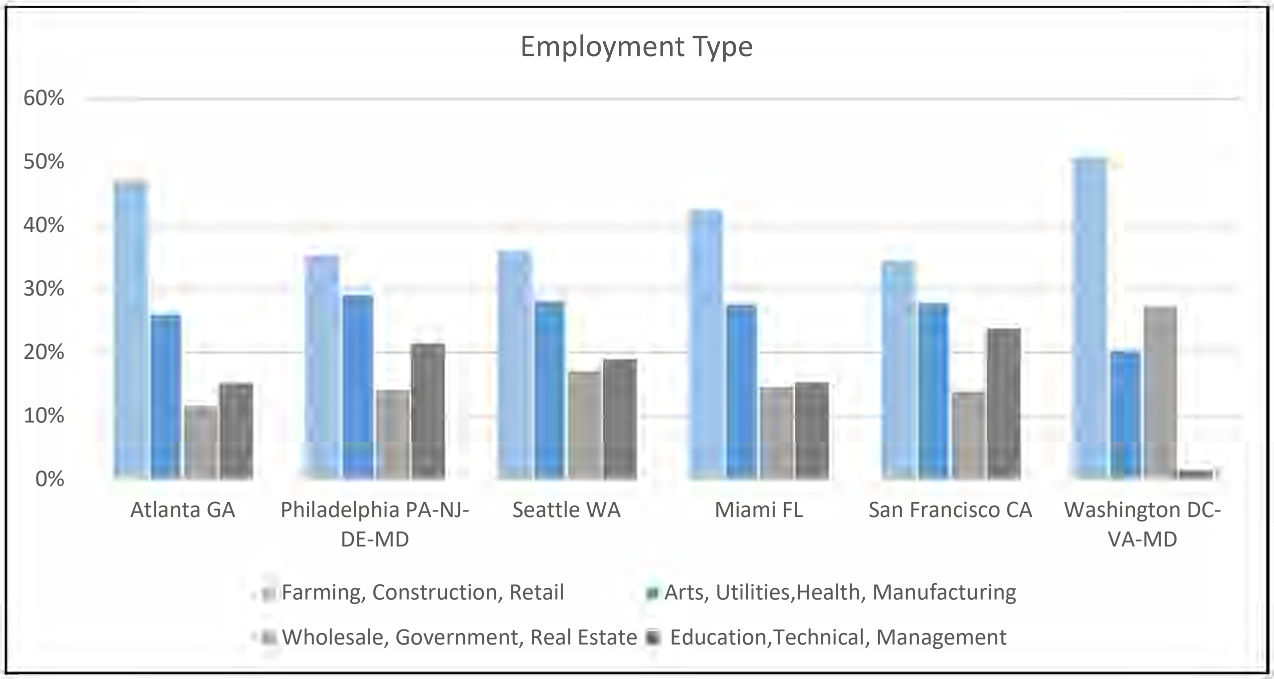

Figure 16. Employment Distribution of Large-Sized Metros

The large metro areas have seen a decrease of 40% on average in public transit ridership, while the VMT has decreased by less than 10% between 2019 and 2022. Heavy railroads account for a high transit mode share of almost 65% in San Francisco, Atlanta, and Washington. By 2022, VMT had declined by less than 12%, and ridership on heavy rail was still less than half of what it was in 2019. In Atlanta, San Francisco, and Washington, the WFH climbed by 5.8%, 9.7%, and 9.5%, respectively, in 2021, as seen in Figure 10.

Except for Washington D.C., all other large-sized metros are approaching 2019 delay levels at a faster rate and could surpass 2019 levels in the next few years. Washington, D.C., witnessed a delay that remained 26% lower than in 2019. One reason the delay has remained lower than in 2019 can be attributed to the unique composition of the city's employment, which has resulted in some of the highest WFH rates in the country. One in three positions in downtown D.C. are held by federal employees, and federal agencies generally offer greater flexibility for remote work. San Francisco is a hub for the tech industry, with companies such as Google, Facebook, and Apple. The delay in 2022 was close to 2019, as many tech companies have started hybrid work models. Atlanta, due to its strategic location and transportation infrastructure, is a center for logistics and transportation-related jobs, and delays in 2022 were found to be 1% greater than in 2019.

Seattle and Miami are mostly dependent on road transport by automobile or bus, and bus ridership in 2022 remains 50% and 20% lower than in 2019. In Miami, the VMT is nearing 2019 levels at a faster rate, and the total delay is 2% higher than in 2019. There was a 3.5% increase in WFH in Miami as opposed to an 8.7% increase in Seattle.

4.5.3 Medium-Sized Metros

Light rail or buses serve as the primary transit modes of transportation in most of the small metro areas with a population of less than 3 million (as shown in Figure 17).

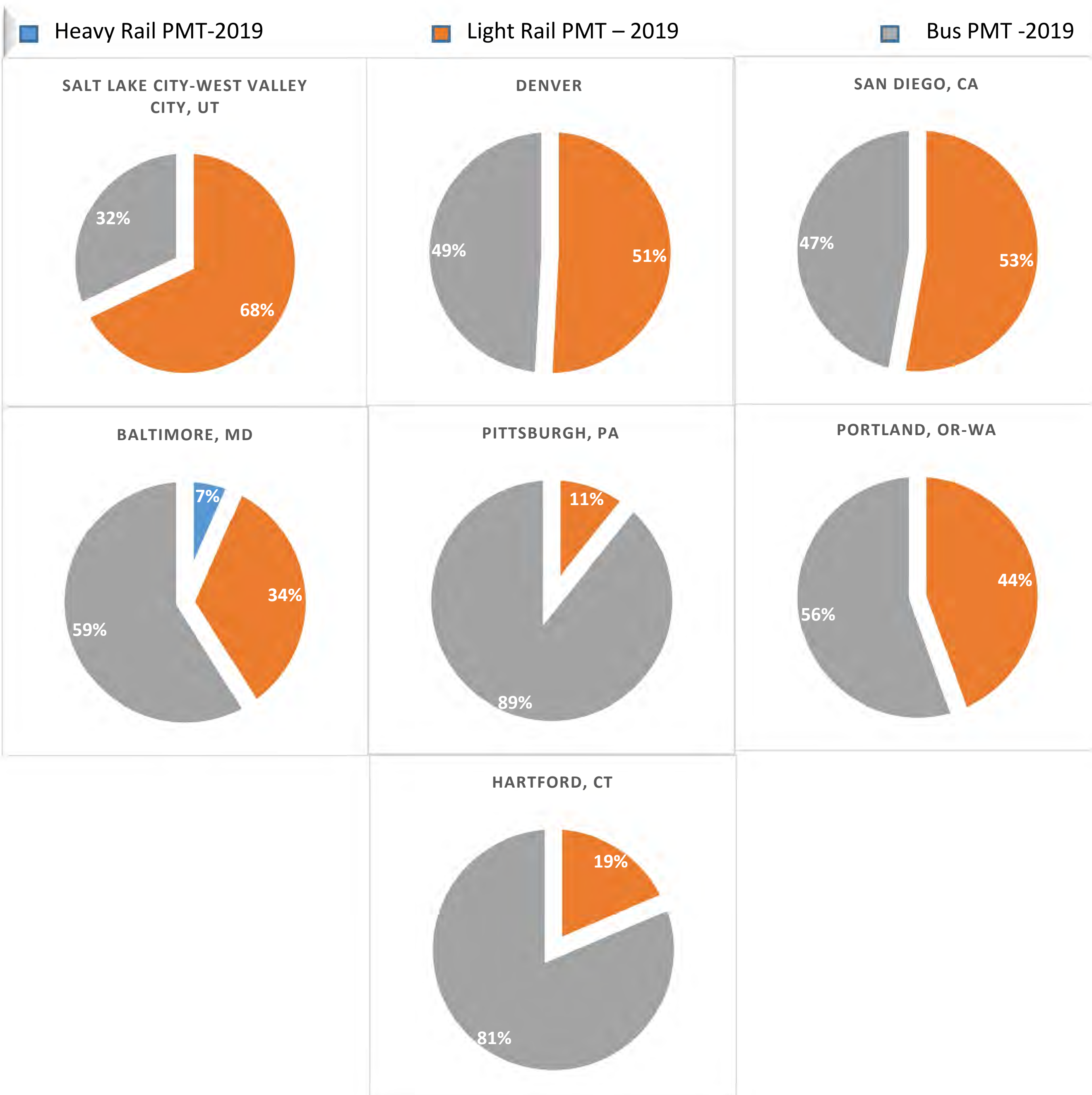

Figure 17. 2019 Transit Share by PMT

Table 14 shows the ridership changes for different transit types in medium-sized metros between the years 2020 and 2022. The ridership changes are expressed as percentages relative to the 2019 ridership levels. The data shows that the COVID-19 pandemic has had a significant impact on ridership across all modes of transportation, with light rail experiencing the largest declines in ridership in most metros. However, some metros, such as San Diego and Pittsburgh, have experienced a slight recovery in ridership. In contrast, urban areas such as Hartford and San Jose continue to experience significant declines in ridership for both light rail and bus modes. In Minneapolis-St. Paul, light rail ridership continued to decline in 2021 but improved slightly in 2022, while bus ridership showed some improvement in both years (Figure 18).

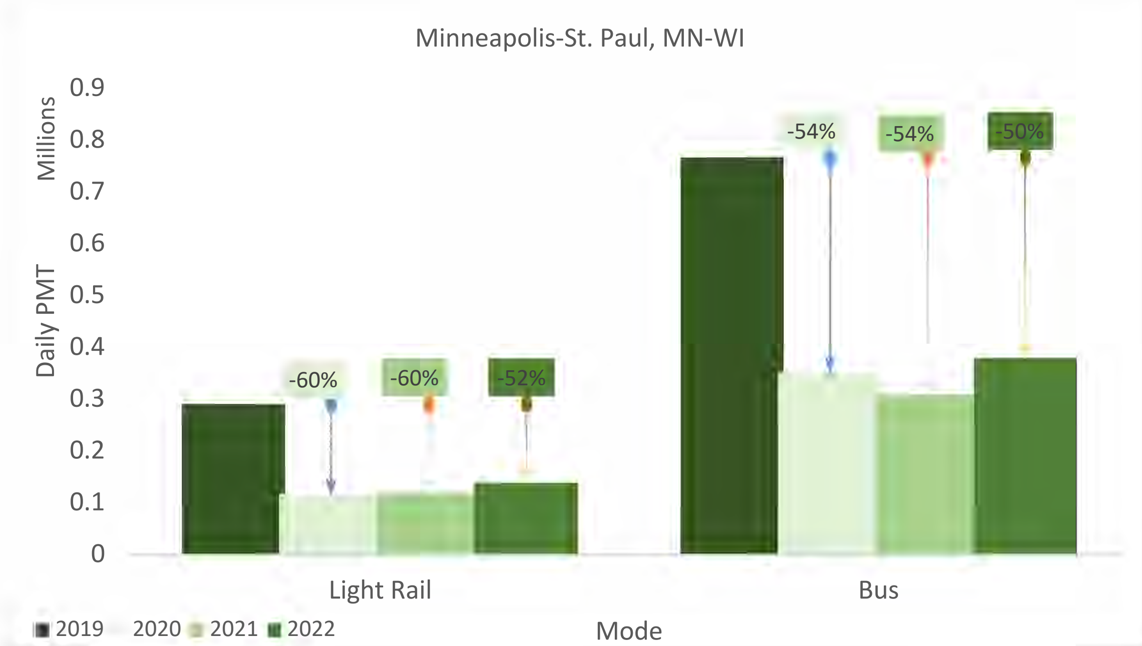

Figure 18. Ridership Change in Minneapolis from 2019 to 2022

Table 14. Change in Ridership in Medium-Sized Metros (2019–2022)

Metros	Modes	2020	2021	2022
Salt Lake City-West Valley City, UT	Light rail	-54%	-53%	-37%
	Bus	-40%	-39%	-22%
Portland, OR-WA	Light rail	-50%	-58%	-46%
	Bus	-47%	-51%	-43%
San Diego, CA	Light rail	-44%	-40%	-14%
	Bus	-49%	-50%	-36%
Baltimore, MD	Heavy rail	-61%	-77%	-76%
	Light rail	-66%	-73%	-63%
	Bus	-38%	-45%	-35%
Denver	Light rail	-55%	-52%	-37%
	Bus	-48%	-55%	-44%
Minneapolis-St. Paul, MN-WI	Light rail	-60%	-59%	-52%
	Bus	-39%	-46%	-32%
San Jose, CA	Light rail	-62%	-78%	-58%
	Bus	-54%	-55%	-36%
Hartford, CT	Light rail	-76%	-82%	-88%
	Bus	-34%	-39%	-30%
Pittsburgh, PA	Light rail	-67%	-73%	-69%
	Bus	-51%	-56%	-43%

Table 15 presents the percentage change in VMT in medium-sized urban areas. The VMT has recovered fully in urban areas like Salt Lake City, Denver-Aurora CO and Pittsburgh PA. This is reflected in the delay numbers in Table 16.

Table 15. Vehicle Miles Travelled – Medium-Sized Metros

Metros	Change in VMT		
	2019-2020	2019-2021	2019-2022
Baltimore MD	-22%	-8%	-6%
Portland OR-WA	-20%		
Salt Lake City-West Valley City UT	-11%	-3%	0%
San Diego CA	-20%	-12%	-9%
Denver-Aurora CO	-14%	-5%	-2%
Hartford CT	-21%	-9%	-6%
Minneapolis-St. Paul MN-WI	-20%	-11%	-9%
San Jose CA	-28%	-15%	-13%
Pittsburgh PA	-19%	-3%	-1%

Table 16. Total Annual Delay – Medium Metros

	Total Annual Delay (1000 Hours)				Percent change from 2019
	2019	2020	2021	2022	2019-2022
Baltimore MD	102,994	44,292	67,052	83,763	-19%
San Jose CA	118,687	46,377	68,269	100,700	-15%
Hartford CT	28,583	16,928	20,702	27,475	-4%
San Diego CA	145,568	55,433	114,993	142,070	-2%
Pittsburgh PA	44,556	24,743	39,001	43,830	-2%
Denver-Aurora CO	111,366	46,181	93,749	110,908	0%
Salt Lake City	29,571	17,124	27,973	31,614	7%
Portland OR-WA	78,309	36,065			
Minneapolis MN	110,297	59,835			

Medium-sized metro areas heavily depend on roads for transportation, and in comparison to very large and large metros, they are witnessing a faster recovery in bus usage. Despite this, there have been significant challenges in public transit ridership in these areas. On average, there has been a substantial decrease of 45% in public transit ridership between 2019 and 2022. In contrast, the decrease in VMT has been relatively modest, standing at less than 13% during the same period.

In Salt Lake City, the delays in commute times have increased by 7% compared to 2019. While VMT has returned to pre-pandemic levels, public transit ridership remains 22% lower in 2022 than it was in 2019. This indicates a considerable disparity between the recovery rates of private vehicle usage and public transportation in the city.

Similarly, in Denver, the delay in commute times has returned to levels similar to those before the pandemic. However, transit usage remains 37% lower than it was in 2019, while VMT has only decreased by 2% compared to pre-pandemic levels. This shows that even though people are driving more frequently, public transit is struggling to regain its pre-pandemic ridership levels.

Pittsburgh's VMT is rapidly approaching the levels seen in 2019, resulting in only a 2% lower traffic delay than that experienced in 2019. Nevertheless, the usage of light rail systems in the city has seen a significant 69% decrease in ridership, and bus ridership is also down by 43% compared to the figures observed in 2019. This indicates a preference for private vehicles over public transit, even as traffic congestion begins to rise.

San Jose stands out among all medium-sized metros, experiencing the highest increase of 10% in work-from-home (WFH) arrangements. As a result, the city has encountered lower delays compared to 2019. However, it's essential to note that public transport ridership still remains lower than in 2019, emphasizing the need to improve public transit services in terms of capacity planning.

As medium-sized metros rely significantly on buses and light rail systems, the situation of low public transit ridership compared to increasing VMT can pose problems for the efficiency of the transportation system. To address this issue, it becomes imperative to focus on enhancing the accessibility, reliability, and connectivity of bus services. Improvements in these aspects can encourage more people to opt for public transportation, reducing traffic congestion, lowering environmental impacts, and contributing to a more sustainable and efficient transportation network.

4.5.4 Comparing Bryan-College Station vs. Austin

Bryan-College Station and Austin can be classified as small-sized metro. The research team intended to compare the transit usage in these two metros home to prominent universities.

Bus is the primary transit type both in Austin and Bryan-College Station. Although light rail is also available in Austin (Figure 21), more than 95% of travelers used buses in 2019, with approximately 383 thousand PMT by buses compared to just 21,782 by L.R. (Figure 20). In Bryan, buses are the only means of public transportation, and TAMU Transit's PMT is 99 percent higher than that of Brazos County.

In contrast to Bryan's PMT of 6,089, TAMU Transit's overall PMT for 2019 was 16,071,627. The reason for this difference in transit usage is mainly due to the fact that Bryan-College Station is home to Texas A&M University, which has a substantial student population. The university provides its own transit services, including buses, which cater primarily to the transportation needs of students within the campus and surrounding areas.

In contrast, while Austin is home to the University of Texas at Austin, the city's public transportation system serves a more diverse population beyond the university campus. Austin experiences significant commuter traffic due to its larger workforce and commuting patterns. Many people commute into the city from the surrounding suburbs and neighborhoods, and public transportation serves as an alternative to driving in congested areas.

In Bryan-College Station, the commuting patterns are less complex, with a more localized population that primarily commutes within the immediate area.

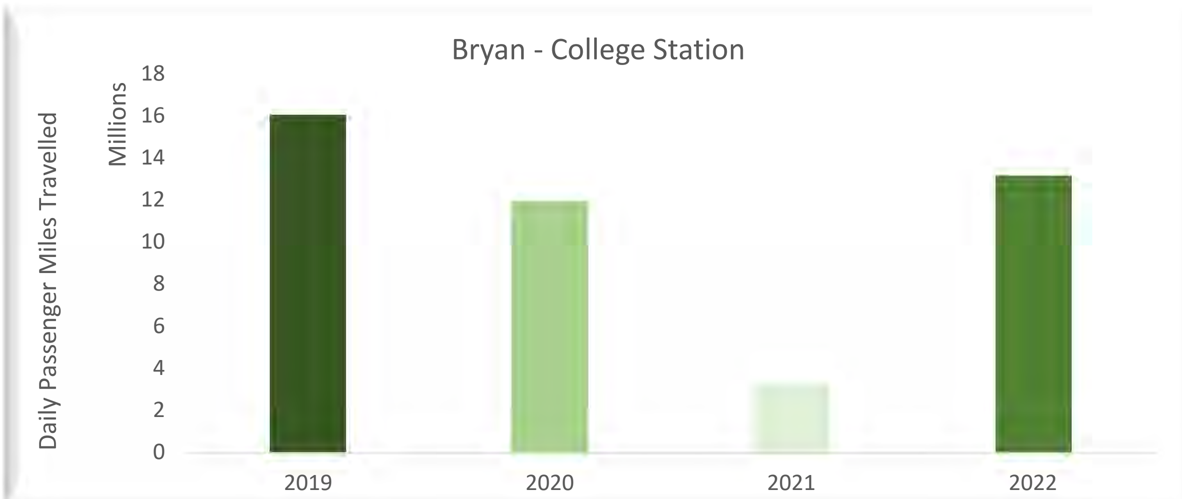

Figure 19. Passenger Miles Travelled in Bryan

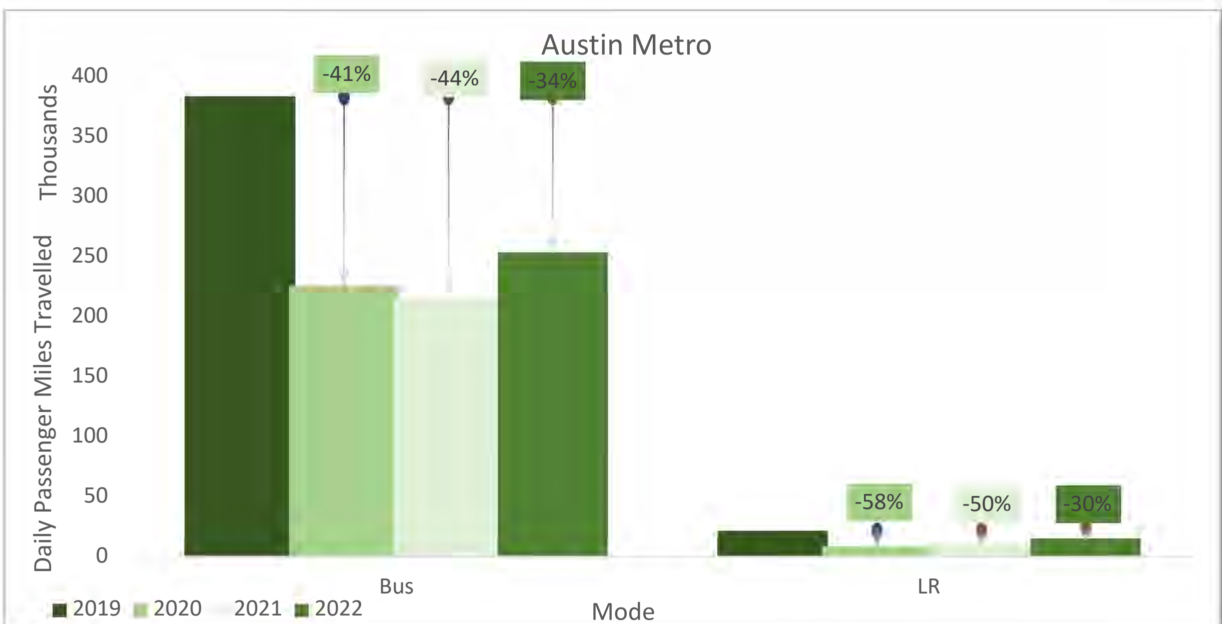

Figure 20. Passenger Miles Traveled in Austin

Chapter 5. Conclusion and Recommendations

The COVID-19 pandemic has had a significant impact on travel behavior and reduced overall travel and transit use. The concern is that the reduction in transit use may lead to congestion in dense urban areas in the long term. This study attempted to investigate post-COVID congestion using extensive traffic and transit data. The research team used National Transit Database (NTD) data to calculate daily passenger miles traveled and vehicle miles traveled for all metros from 2019 to 2022. The top 18 metros with highest transit ridership were selected for detailed analysis.

The pandemic has affected public transit ridership differently across different modes of transit and metropolitan areas. There has been some recovery in public transit ridership for the very large metro areas as we come out of the pandemic, but it has been modest and much slower than auto travel recovery. Auto delay and VMT decreased dramatically in 2020, and in 2022 it has returned and is close to 2019 levels.

There has been some recovery in public transit ridership for the large metro areas over the last two years, but it has typically been slower to return than public transit ridership in the very large metro areas and much slower than auto travel recovery as well. VMT decreased dramatically in 2020, and in 2022 it has returned and is close to 2019 levels. The delay has also returned to the 2019 levels in large metro areas except for Washington DC, where there appears to be a much higher level of work from home than other large metro areas.

Medium-sized metros are typically more reliant on bus mode than larger metro areas, and they have continued to experience higher reductions in ridership than larger metro areas. VMT in the medium-sized areas is approaching the 2019 levels, but it still tends to be lower than in 2019. The delay in the medium-sized areas has returned to the 2019 levels except for Baltimore and San Jose. Medium areas tend to be less congested and experience less systemic delay than the larger metro areas.

Future travel patterns: Based on the current trends, it appears that the levels of delay in some of the large metropolitan areas are returning to what they were in 2019. However, these delays are taking on different forms compared to pre-pandemic times. One significant factor contributing to this change is the increased flexibility in work schedules and the rise of remote work, which has led to some decreases in travel during traditional peak times. In 2020, due in part to the flexibility offered by remote work, there was a higher share of overall delay during mid-day hours. This means that congestion during the middle of the day increased, while the morning and evening peak hours experienced relatively lower levels of congestion compared to 2019. As the situation evolves, it appears that the evening peak is returning approximately to pre-pandemic levels, indicating a resurgence in commuter traffic.

However, the morning peak is still below 2019 levels, suggesting that fewer people have returned to their regular commuting patterns. Additionally, there seems to be more congestion between the morning and evening peaks, indicating a shift in travel patterns. The delay in metros that are home to technology companies, which had dropped considerably, is now returning to 2019 levels. This trend is attributed to the increasing adoption of Hybrid Work-From-Home (WFH) arrangements by many tech companies. While the research team lacks the latest data on WFH trends, it is evident that the transition from full-time remote work to a hybrid model is already impacting commuter travel behavior and the overall transportation landscape. Hybrid WFH involves a combination of in-office work and remote work, where employees are required to attend physical offices only on certain days of the week, rather than adhering strictly to the traditional 9 am to 5 pm working hours.

This flexible work schedule gives employees the freedom to manage their time more efficiently and avoid peak-hour rushes, resulting in reduced pressure on the transportation system during traditional rush hours. The adoption of Hybrid WFH has the potential to reshape traffic patterns in the future. With employees commuting on different days and at varying times, the predictable peak hours may become less pronounced, and there may be a redistribution of travel demand throughout the day. This change in commuting patterns will require transit systems to adapt and reschedule their services accordingly.

The rate of ridership recovery and growth in metropolitan areas depends on various factors, including the existing infrastructure. Overall, larger metros with extensive transit systems, such as those in New York and Chicago, are expected to recover faster than medium-sized metros that rely primarily on light rail or buses for transportation. This is because the availability of more transit options encourages additional commuters to use public transportation, reducing congestion on roads.

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