The Impact of COVID-19 & Safer-at-Home Policies on US Public Transit

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ABSTRACT

COVID-19 has affected travel behavior and disrupted public transit usage. This paper investigates the short-term impact of COVID-19 and safer-at-home policies on public transit ridership and vehicle usage in the US. Using monthly data from the National Transit Database between January 2012 and June 2020, this paper finds that ridership has decreased by 67 to 71 percent. Similarly, vehicle usage in terms of number of hours and miles travelled has decreased by 43 to 45 percent and 46 to 48 percent respectively post the incidence of COVID-19. Interestingly, there is heterogeneity in terms of ridership across different modes of transport. Smaller modes faced greater decrease in ridership, while 'demand driven' modes experience increase in ridership. Using variation in implementation of safer-at-home policies across states, this paper also finds that these policies did not cause a statistically significant decrease in public transit ridership and vehicle usage. The findings and the possible policy implications are briefly discussed.

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1 Introduction

Since the end of 2019, the world has been dealing with a new type of infectious disease, a severe acute respiratory syndrome coronavirus (SARS-CoV-2 by the International Committee of Taxonomy of Viruses). It was later renamed as Coronavirus Disease-19 or COVID-19 (World Health Organization, 2020a). By the end of September 2020, COVID-19 has infected more than 34 million people globally and claimed the lives of more than 1 million deaths (John Hopkins University, 2020).

According to World Health Organization (2020b), the virus spreads through respiratory droplets and/or surface contact. Therefore, to prevent further spread of the virus, countries adopted several public health measures, including social distancing (Fong et al., 2020). The social distancing spectrum has varied considerably across countries, ranging from voluntary compliance (e.g., Sweden) to complete lockdowns (e.g., China, Italy and Spain). Nevertheless, together with spontaneous reductions in economic activity by consumers and producers alike, lockdowns and other social distancing measures have led to a global economic shock triggering recession across countries (World Bank, 2020). The International Monetary Fund (2020) downgraded its forecast to 4.9 percent contraction in global economy in June 2020 from 3 percent contraction in April 2020. The Fund cited: i) longer persistence in social distancing; ii) slower economic activity during lockdowns; and iii) greater decline in firm productivity than expectation as some of the reasons for the downgrade. Therefore, there is continued uncertainty about the future, especially about pandemic induced shifts in consumption, travel and other discretionary spending (Altig et al., 2020; Baker et al., 2020).

COVID-19 has deeply affected the United States of America (US). The first confirmed case of COVID-19 in the US was detected on January 19 (Holshue et al., 2020). However, since March 26, the country has the highest number of COVID-19 cases and subsequently deaths in the world (John Hopkins University, 2020). In response to the COVID-19 crisis, the US did not impose a national lockdown. This is because within states the US President and the federal government have limited powers and only state governors have the authority to impose state-wide lockdowns (Wetter & Gostin, 2020). US state officials gave state-wide lockdown orders or implemented safer-at-home policies from the middle of March 2020.[1] These orders meant that travel was restricted only for essential purposes, mass gatherings were prohibited, schools and businesses were shut down and people were expected to work from home, where possible. However, not all US states implemented safer-at-home policies.[2]

COVID-19 has disrupted travel behavior and public transit system in the US. There has been a massive drop in ridership. During this time, only essential workers (e.g., doctors, nurses, other hospital employees, retail employees and other frontline workers) have continued to utilize these services. The decrease in ridership has in turn reduced transit services, vehicle usage and revenue earnings for transit agencies (Wanek-Libman, 2020).[3] While fares and ridership-related funds are transit agencies' largest sources of revenues, other key sources have also declined significantly due to underlying economic conditions. According to a report by the American Public Transportation Association (APTA), these revenue sources include state and local taxes, as well as motor fuel tax revenues. At the same time, transit agencies are facing increase in costs to safeguard against COVID-19 (e.g., purchasing personnel protective equipment, continuous cleaning of vehicles, emergency staffing etc.).

The falling revenue and increased costs have resulted in significant negative financial impact for transit agencies. In response to COVID-19, the US Congress enacted, and President Donald Trump signed into law, the Coronavirus, Aid, Relief and Economic Security (CARES) Act, a US$ 2 trillion relief package to support the economy (Courtney, 2020). The CARES Act allocated US$ 25 billion to transit agencies through the Federal Transit Administration (FTA) to support capital and operating expenditures during the COVID-19 pandemic. However, the CARES funding may not be sufficient to meet the funding requirements of the transit agencies in the long run. According to TransitCenter (2020), the estimated financial impact on US

[1] In the context of this paper, the terms "lockdowns", "stay-at-home orders" and "safer-at-home policies" mean the same and the terms might be used interchangeably.

[2] Baccini and Brodeur (2020) analyze the implementation of safer-at-home policies at the state level based on governor's characteristics and find that political ideology (i.e. Republican or Democrat) and term limits are the most important factors in implementation of lockdowns.

[3] According to EPB (2020), many transit agencies have stopped collecting fares onboard buses/trains since March 2020 to minimize surface contact between riders and transit operators. This has also negatively affected transit agency revenue.

transit agencies range between US$ 26 to US$ 40 billion annually, far more than the monetary support provided under the CARES Act.[4]

Due to the enormous financial and economic impact, identifying the impact of COVID-19 and safer-at-home policies on ridership and vehicle usage is crucial. However, it is difficult to quantify the impact for several reasons. There is a possibility of reverse causality. Increase in COVID-19 cases across states might have deterred public transport ridership and subsequently vehicle usage. However, public transit ridership might have caused propagation of COVID-19 cases. There might also be omitted variable bias in terms of factors not taken into account. Moreover, there might be variation in ridership and vehicle usage across different modes of public transit. For example, this could be due to behavior difference of riders (they might prefer trains compared to buses as there might be more space to socially distance). It could also be due to differences in decision making amongst transit agencies (some transit agencies might not wish to reduce services while others might do so). In terms of safer-at-home policies, most analysis highlights a year-on-year before and after comparison (e.g., ridership in May 2020 compared to May 2019). These type of analysis does not help identify the causal effect of the policy as it does not account for the heterogeneity between US states.

This paper investigates the short-term causal impact of COVID-19 and safer-at-home policies on US public transport ridership and vehicle usage. The study uses data from the National Transit Database (NTD), which has monthly information on ridership and vehicle usage between January 2002 and June 2020 across different states at the transit service level. To assess the impact of COVID-19, this paper conducts a simple pre/post analysis of public transit ridership and vehicle usage. In addition, to overcome the difficulties in assessing the causal impact of safer-at-home policies, this paper utilizes a difference-in-differences (DID) framework by accounting for the variation between states which did and did not implement safer-at-home policies in response to COVID-19.

The pre/post regression results show that overall, there is a 67 to 71 percent fall in public transit ridership post the incidence of COVID-19. Similarly, there is a decrease number

[4] See Fortunati (2020) for further details on the distribution of CARES Act funding to transit agencies and long-term fund requirements.

in public transit vehicle usage in terms of number of hours (43 to 45 percent) and number of miles travelled (46 to 48 percent) post incidence of COVID-19. The results are statistically significant at the 1 percent level. The decrease in ridership and vehicle usage does not depend on the service provider (i.e., whether transit agencies operate by themselves or through private third party operators). Moreover, there is variation across modes. Smaller modes experienced greater decrease in ridership, while others saw increase in ridership and vehicle usage after the incidence of COVID-19. The later are mostly 'demand-driven modes', i.e., they are non-scheduled and are called into service when required. The DID results show that implementation of safer-at-home policies did not cause a statistically significant fall in public transit ridership and vehicle usage.

The literature on the impact of COVID-19 and subsequent stay-at-home orders has grown significantly since the start of the pandemic.[5] This study adds to the emerging literature on the economic effects of COVID-19 and safer-at-home policies in the US (e.g., Abouk and Heydari (2020), Alvarez et al. (2020), Atkeson (2020), Baker et al. (2020), Béland et al. (2020), Binder (2020), Coibion et al. (2020), Farboodi et al. (2020)). This paper also contributes to the literature on the impact of COVID-19 and lockdown on transportation. Some studies have documented the impact of COVID-19 on public transit ridership (e.g., Arellana et al. (2020), Park (2020), Jenelius and Cebecauer (2020)).[6] Other studies have analyzed the effect of COVID-19 across travel behavior (e.g., De Vos (2020)) and socio-economic groups (e.g., Brough et al. (2020), DeWeese et al. (2020), Wilbur et al. 2020)). However, to the best of knowledge, this is the first study documenting the effect of COVID-19 and safer-at-home policies on public transit ridership and vehicle usage in the US using the NTD data and a regression framework.[7]

[5] See Brodeur et al. (2020a) for a detailed literature review on the economic implications of COVID-19 and safer-at-home policies.
[6] In an earlier study, Wang (2014) explore the public fear of utilizing public transport in Tapei, Taiwan during the peak of severe acute respiratory syndrome (SARS) epidemic in 2003.
[7] The closest comparable study in the US is Wilbur et al. (2020). The authors assess the impact on ridership for Nashville and Chattanooga in the state of Tennessee using data from the Metropolitan Government of Nashville, Davidson Count and Chattanooga Area Regional Transportation Agency. Outside the US, Park (2020) examines the change in ridership of Seoul Metropolitan Subway after implementation of social distancing measures in Seoul, South Korea using data from each of the transit authority. Jenelius and Cebecauer (2020) assess the impact of COVID-19 on public transit ridership in Stockholm, Västra Götaland and Skåne of Sweden. The ridership

The rest of the paper is structured as follows. Section 2 discusses the conceptual framework of how COVID-19 has affected US public transport ridership and vehicle usage. Section 3 describes the data from the NTD of the US Department of Transportation and safer-at-home policies implemented across US states. Section 4 elaborates on the identification strategy. Section 5 presents the findings & results for ridership and vehicle usage from the pre/post and DID regressions. Section 6 provides the conclusion to the paper. Sections 8 and 9 contain the figures and tables respectively.

2 Conceptual Framework

The economic benefits of public transportation are manifold. Investment in transit can create 49,700 jobs per $US 1 billion invested and offers a five-fold economic return on investment (Hughes-Cromwick, 2020). [8] Nevertheless, public transport has taken a major hit after COVID-19 and safer-at-home policies in US. It is difficult to quantify the effect of specific events on people's movement. However, there has been an increasing use of cellphone location data to measure mobility of population.[9] Several authors have utilized these mobility data to examine the effect of COVID-19 and safer-at-home policies on mobility patterns (e.g., Abouk and Heydari (2020), Askitas et al. (2020), Béland et al. (2020). Others have used mobility data to examine compliance with safer-at-home policies, including factors associated with compliance (e.g., Allcott et al. (2020); Barrios and Hochberg (2020); Briscese et al. (2020), Brodeur et al. (2020b); Wright et al. (2020)). Some researchers have used mobility data to examine the impact of safer-at-home policies on pollution, traffic, car accidents (e.g., Brodeur et al. (2020c); He et al. (2020)). Mobility data includes travel to transit stations, which has also been examined by researchers. For example, Jacobsen and Jacobsen (2020) found that 26 states which implemented safer-at-home policies during March 2020 experienced a 53

numbers are based on ticket validation data at stations for subways and automatic passenger counting sensors aboard buses.

[8] Bhatta and Drennan (2003) provide a detailed literature review on the long-term economic benefits of public transportation.

[9] Brodeur et al. (2020a) examine the differences between mobility data compilation by data providers. They also assess the pros and cons of utilizing mobility data.

percent decrease in mobility to transit stations compared to 39 percent decrease for 25 states which did not implement safer-at-home policies at the time.

However, movement to transit stations is not the same as public transit ridership and vehicle usage. Transit agencies record passenger ridership and vehicle usage in terms of hours in service and miles travelled. According to Dickens and Grisby (2020) from the APTA, ridership across US public transports has decreased by 70 percent or more during March 2020 compared to the same month in 2019.[10] It is expected that public transport will play a critical part in getting economies moving again post COVID-19 (Ardila-Gomez, 2020). Therefore, it is important to formally assess the channels through which COVID-19 and subsequent safer-at-home policies effected usage of public transportation. This paper tries to identify some of the channels which have affected public transit ridership and vehicle usage.

The first channel is that the risk of contracting COVID-19 negatively affects demand for transit trip. The demand for a transit trip can be viewed as a function of both the utility of the trip and its costs: time (access time, wait time, travel time), money (transit fare), and uncertainty (schedule adherence, safety, etc.) (Taylor et al., 2009). Several researchers have provided evidence that COVID-19 spreads through airborne transmission (e.g., Buonanno et al. (2020), Edelson and Phypers (2011), Nishiura et al. (2020)). COVID-19 may also spread through surface contamination (e.g., Musselwhite et al. (2020)) and can be transmitted by asymptomatic patients (e.g., Gandhi et al. (2020)). These factors pose risks for passengers in public transit as they are confined in a limited space and are in contact with multiple surfaces (e.g., seats, handrails, doors) that can easily transfer the virus (Tirachini & Cats, 2020). Other researchers examined COVID-19 transmission through public transit. Hu et al. (2020) study COVID-19 transmission across high speed trains and find that there is a high risk of transmission with variation between seat location and co-travel time between passengers. Zhang et al. (2020) show that there is a significant association between the frequency of high-speed train out of Wuhan, China and the COVID-19 cases in the destination cities. The further the destination cities are from Wuhan, the lower the number of COVID-19 cases. Harris (2020) conjectures that the New York City subway has been major propagator of COVID-19 during

[10] Hendrickson and Rilett (2020) attribute the decrease to the human aspect of transportation system.

the initial rise of cases in March 2020. The author suggests that the subsequent decline in subway usage strongly correlates with the reduction in COVID-19 cases. These risks and the related uncertainties might outweigh the benefit or utility derived from the transit trip. As a result, it might have decreased demand for public transit post COVID-19.

The second channel is through the economic consequences of lockdowns. A number of studies have focused on these economic consequences, particularly in terms of labor market implications (e.g., Adams-Prassl et al. (2020), Béland et al. (2020), Coibion et al. (2020)). For example, Gupta et al. (2020) find that, after accounting for cross-state variation in the timing of business closures and stay-at-home mandates, employment rate in the US fell by 1.7 percentage points for every extra 10 days that a state experienced lockdowns during the period of March to April. Increase in unemployment might account for the reduction in public transit usage. Moreover, differences in type of work and income might explain the variation between usage between different groups of public transit users.[11] According to Tan et al. (2020), even though both high and low income workers use public transportation to get to work, the key difference is highly-paid workers are also more likely to be able to work remotely, making them less likely to demand public transit during this time. On the other hand, low income workers might not be able to work remotely and have to rely on public transport to reach their workplace.

The third channel is through the implementation of safer-at-home and other policies which lead to reduction of out-of-home activities. According to De Vos (2020), safer-at-home policies have reduced out-of-home activity participation. As a result, household members are expected to perform daily activities from home. Moreover, many companies have adopted work from home policy for an indefinite period and some companies have asked employees to refrain from using public transport to stop the spread of the virus (Mitchell, 2020). Lack of activities coupled with work from home orders have decreased demand for public transit. While restrictions are being lifted across US states, participation in public activities might not

[11] Béland et al. (2020) show that occupations that have a higher share of workers working remotely were less affected by COVID-19 lockdowns. On the other hand, occupations with relatively more workers working in proximity to others were more affected. They also find that occupations classified as 'more exposed to disease' are less affected, which is possibly due to the number of essential workers in these occupations.

return to pre-COVID-19 levels, at least in the short run. Therefore, demand for public transit might remain depressed till that time.

The fourth channel is through substitution effect. Some studies have documented the increase usage of different modes of transport during the pandemic such as personal cars, ridesharing services such as Uber or Lyft, bicycle and others. During the 2002-2004 SARS outbreak, there was a rise in electronic bike (e-bike) usage in China (Simha, 2016). Teixeira and Lopes (2020) find evidence that there is a modal transfer from usage of subway in New York City to bike sharing systems. Bucsky (2020) also find that there is modal split through decline in share of public transport usage and increase in usage of road transport via cars in Budapest. Ivaldi and Palikot (2020) find increase in ridesharing service usage post re-opening in France. Therefore, the availability of alternative modes of transport might explain the decrease in public transit ridership.

3 Data

3.1 National Transit Database (NTD)

The NTD data is retrieved from the FTA of the US Department of Transportation. The NTD was set up as the repository of data about the financial, operating and asset conditions of US transit systems. It contains information on agency funding sources, inventories of vehicles and maintenance facilities, safety event reports, measures of transit service provided and consumed, and data on transit employees. The NTD collects information from the individual transit agencies. These transit agencies serve either an Urbanized Area (UZA) or a rural area.[12] All transit properties that are recipients of Urbanized Area Formula Grants and eligible to receive funding from the CARES Act through the FTA are required to report ridership and vehicle usage data. Therefore, at the end of each month, individual transit agencies have the next one month to compile and submit the data to the NTD. The submissions are reviewed by

[12] UZAs are defined by the US Census Bureau as areas with a population of 200,000 or more.

the FTA for accuracy and reasonableness. As a result, the data is available on a monthly basis by mode and type of service (TOS) for a fiscal year.[13] The data is described below.

The NTD database contains data on four key variables: i) unlinked passenger trip (UPT); ii) vehicle revenue hours (VRH); iii) vehicle revenue miles (VRM); and iv) vehicle operated in maximum service (VOMS).[14] UPT shows the number of passengers who board public transit vehicles. The count is shown each time a passenger boards a public transit vehicle, no matter how many vehicles are needed to reach the destination from origin. VRH is the number or hours that a public transit vehicle travels while in revenue service. VRM is the number of miles that a public transit vehicle travels while in revenue service. VOMS is the number of revenue vehicles in operation to meet the maximum service requirement. This count is based either on the number of vehicles in operation during peak season of the year or on the week and day that maximum service is provided. For the purposes of this analysis, VOMS is not utilized as a variable. This is because COVID-19 related disruptions are not expected to affect the maximum number of vehicles, at least in the short turn. UPT is used to measure ridership. On the other hand, VRM and VRH are used to assess vehicle usage. Table 1 provides the summary statistics for UPT, VRH and VRM.

The UPT, VRH and VRM data are reported according to several modal classifications. The bus services are categorized as: i) Articulated Bus (AB); ii) Commuter Bus (CB); iii) Fixed Route bus (MB); iv) Bus Rapid Transit (RB); and v) Trolley Bus (TB). The rail services are categorized as: i) Alaska Railroad (AR); ii) Cable Car (CC); iii) Inclined Plane (IP); iv) Heavy Rail (HR); v) Light Rail (LR); vi) Streetcar (SR); vii) Monorail (MO); viii) Monorail/Automated Guideway (MG); and ix) Hybrid Rail (YR). Apart from bus and rail services, there are other modes such as: i) Ferry Boat (FB); and ii) Aerial Tramway (TR). In addition, there are non-scheduled services. These are provided by transit agencies when there is demand for them i.e. 'demand-driven' services. These can be either bus or rail services and include: i) Demand Response (DR); ii) Demand Taxi (DT); iii) Publico (PB): and iv) Vanpool (VP). The NTD also reports all modes as one of two types of service (TOS): i) Directly Operated (DO); and ii)

[13] The data is available at: https://www.transit.dot.gov/ntd/data-product/monthly-module-adjusted-data-release

[14] The definitions are gathered from: https://www.transit.dot.gov/ntd/national-transit-database-ntd-glossary

Purchased Transportation (PT). DO service is provided directly by the transit agency. On the other hand, PT means that the service is contracted from third parties, which are usually private operators.

3.2 Safer-at-Home Policies

The safer-at-home policies data at the state level is derived from Mervosh et al. (2020) of the New York Times.[15] Table 1 shows the lockdown announcement, start dates, expiry dates for states across US. As it can be seen, there is considerable variation in the implementation of safer-at-home policies. At the daily level, the first state to implement lockdown was California on March 19, 2020. Subsequently, 18 states followed suit during the next weeks. However, at the monthly level, most states implemented safer-at-home policies within March and April. By the end of April, 43 states, including the District of Columbia, had implemented state-wide lockdowns. However, eight states – Arkansas, Iowa, Nebraska, North Dakota, South Dakota, Oklahoma, Utah and Wyoming – did not implement state-wide safer-at-home policies between March and April 2020.

4 Identification Strategy

4.1 Identification Strategy: Before & After COVID-19

To assess the impact of COVID-19 on public transit ridership and vehicle usage, this paper conducts a simple pre/post analysis. The model is:

$$Y_{m,a,t} = \alpha + \beta POSTCOVID_t + \emptyset POSTCOVID_t * MODE_{m,a,t} + \gamma POSTCOVID_t * TOS_{m,a,t} + \delta MODE_{m,a,t} + \mu TOS_{m,a,t} + \varphi_a + \theta_t + \varepsilon_{m,a,t} \quad [1]$$

where $Y_{m,a,t}$ is the outcome variable – UPT, VRH and VRM – for mode *m* operated by transit agency *a* at month *t*. The time period is between January 2012 to June 2020. $POSTCOVID_t$ is a dummy variable equal to 1 after COVID-19 cases started increasing in the US (i.e., for March, April, May and June 2020) and 0 in the preceding months. β is the coefficient for $POSTCOVID_t$.

[15] This paper considers the impact of the safer-at-home policies/lockdown implemented between March and April 2020. US states subsequently started re-opening from May 2020 and onwards. The data on re-opening is available at: https://www.nytimes.com/interactive/2020/us/states-reopen-map-coronavirus.html

$MODE_{m,a,t}$ and $TOS_{m,a,t}$ are vectors of regressors which include modal and TOS fixed effects, respectively. These fixed effects represent different modes and service providers. To account for the heterogeneity in ridership and vehicle usage across modes and TOS, this analysis includes the interaction terms $POSTCOVID_t * MODE_{m,a,t}$ and $POSTCOVID_t * TOS_{m,a,t}$. This is shown by the coefficient $\emptyset$ and γ respectively. φ_a represents transit agency fixed effects to account for time invariant transit agency characteristics. θ_t represents month and year fixed effects. $\varepsilon_{m,a,t}$ is the random error term. The standard errors are clustered at the transit agency level.

4.2 Identification Strategy: DID Framework

To estimate the impact of safer-at-home policies, this paper uses a DID strategy by comparing states that implemented these policies with those that did not. The DID model is:

$$Y_{m,a,t} = \alpha + \beta POSTSAFER_t + \omega TREATEDSAFER_{s,t} + \delta MODE_{m,a,t} + \mu TOS_{m,a,t} + \varphi_a + \theta_t + \varepsilon_{m,a,s,t} \quad [2]$$

where $Y_{m,a,t}$ is the outcome variable – UPT, VRH and VRM – for mode *m* operated by transit agency *a* at month *t*. The time period is between January 2012 to June 2020. $POSTSAFER_t$ is a dummy variable equal to 1 after the introduction of a safer-at-home policies were implemented in the US (i.e., for April, May and June 2020) and 0 in the preceding months. As noted earlier, some states implemented safer-at-home policies while others did not. States implementing the policy are classified as the treatment group, while states which did not implement the policy are classified as control group. Therefore, in this specification, $TREATEDSAFER_{s,t}$ is the interaction term between treated group and $POSTSAFER_t$. ω is the coefficient of interest in Equation [2]. As before in Equation [1], $MODE_{m,a,t}$ and $TOS_{m,a,t}$ are modal and TOS fixed effects. φ_a represents transit agency fixed effects to account for time invariant transit agency characteristics. θ_t represents month and year fixed effects. $\varepsilon_{m,a,s,t}$ is the random error term. The standard errors are clustered at the state level, the level at which most of the safer-at-home policies were implemented.

The identification assumption is that, conditional on controls, the evolution of UPT, VRH and VRM for states with safer-at-home policies would not be different compared to states without the policies. This is equivalent to the 'parallel trends assumption' for ridership and vehicle usage between treated and control states.

5 Effect of COVID-19, Safer-at Home Policies on Ridership & Vehicle Usage

This section analyzes the impact of COVID-19 and safer-at-home policies on public transit ridership and vehicle usage, i.e., UPT, VRH and VRM. This is done through: i) graphical analysis before and after COVID-19 cases started in the US; ii) pre/post regression analyzing the effect on ridership before and after COVID-19; and iii) DID strategy using states which did and did not implement safer-at-home policies.

Table 2 shows the summary statistics for transit ridership and vehicle usage. The table shows the number of observations, mean, standard deviation, maximum and minimum values for UPT, VRH and VRM. In particular, there is variation in the number of observations between ridership (UPT) and vehicle usage (VRH and VRM). This is because the final dataset dropped all the observations between January 2002 to June 2020 for a specific mode of transit agency if there was no data available post COVID-19 i.e. for March, April, May and June 2020.

5.1 Graphical Analysis

Figure 1 shows UPT in terms of average number of passengers riding on public transit across all modes each month. As it can be seen, UPT experiences a cyclical trend in a particular calendar year, with peaks in October and troughs in February. During 2020, there was a significant fall in UPT from February and onwards, one month after the first case of COVID-19 was detected in the US. Figure 2 shows UPT in terms of average number of passengers each month for the top four modes of transit, i.e., CB, DR, MB and VP. As it can be seen, the fall in ridership is uniform across the most utilized modes of transit. Notably, there is a slight uptick in ridership in June 2020.

Figures 3 and 4 show VRH and VRM in terms of average hours of service and average miles travelled across all modes each month, respectively. VRH and VRH also experience a cyclical trend with peaks in October and troughs in February. Figures 5 and 6 show VRH and VRM in terms of average hours of service and average miles travelled each month for the top four modes of transit respectively. Both figures show that vehicle usage experienced significant drop across the top five modes of public transit.

5.2 Pre/Post Regression Analysis

Tables 3, 4 and 5 present the results of Equation 1. In all columns, the dependent variable is in logarithms of UPT, VRH and VRM, respectively. Moreover, all columns include agency fixed effects. Column 1 shows the results without the interaction term and includes only agency, month and year fixed effects. Column 2 shows the results without the interaction term; however, it includes mode and TOS fixed effects along with agency and time fixed effects. Column 3 includes the interaction term between $POSTCOVID$ and TOS, which are owned and operated by the agencies directly i.e. DO. Column 4 includes only the interaction term between $POSTCOVID$ and *MODE*. Column 5 includes both the interaction terms for $POSTCOVID$ and *MODE* and $POSTCOVID$ and TOS.

Table 3 shows the results for the impact of COVID-19 on public transit ridership. In all columns, the estimates for $POSTCOVID$ are negative and statistically significant at the 1% significance level. This shows that post COVID-19 during March, public ridership decreased between 67 to 71 percent, depending on the specifications in the equations.[16] In Column 3, the interaction term between $POSTCOVID$ and *TOS* is negative and not statistically significant at conventional levels. This suggests that there is no differential effect in ridership in terms of *TOS* (i.e., whether the public transit riders use a service which are owned and operated by the agencies directly or by third-parties). The results in Columns 4 and 5 focus on the interaction term between $POSTCOVID$ and *MODE*. Interestingly, there is variation in decrease across different modes and not all the modes experienced statistically significant decline in ridership. Modes that serve a small segment such as AR, MG and PB saw greater declines in ridership. The 'demand driven' modes such as DR and VP gains in ridership post the incidence of COVID-19. The increase in ridership is statistically significant at the 5 and 10 percent, respectively.

Tables 4 and 5 shows the results for the impact of COVID-19 on public transit vehicle usage hours and miles travelled during service respectively. In Table 4, the dependent variable is the log of VRH. In Table 5, the dependent variable is the log of VRM. As it can be seen, the

[16] The percentage increase or decrease from a logarithmic equation is derived according to the formula: [*exp*(coefficient value)-1] x 100%.

estimates of $POSTCOVID$ are negative in both tables. This suggests that there is a decrease in number of hours and miles travelled during the post COVID-19 period. For Columns 1 to 3 in Table 4, the decrease is around 43, 43 and 45 percent respectively. Similarly, for Columns 1 to 3 in Table 5, the decrease is around 46, 46 and 48 percent respectively. These estimates are significant at the 1 percent level. In Column 3 of both tables, the interaction term between $POSTCOVID$ and *TOS* is positive and statistically significant at conventional levels. However, in Column 5, the estimates for the interaction term are negative but statistically not significant. This suggests that the decrease in hours of services and miles travelled is not related to the *TOS* of the transit agencies. For both tables, the estimates for the interaction term between $POSTCOVID$ and *MODE* are in Columns 4 and 5. They show that vehicle hours and miles travelled for AR, IP and PB experienced a significant drop in hours of usage post COVID-19, while other modes such as CC and CB experienced lower fall in usage. Notably, unlike ridership, there is no statistically significant increase in vehicle usage post the incidence of COVID-19.

5.3 DID Analysis

Tables 6, 7 and 8 present estimates of Equation 2. In all columns, the dependent variable is the log of UPT, VRH and VRM, respectively. Column 1 shows the estimates with only time fixed effects. Column 2 shows the estimates with agency, month and year fixed effects, while Columns 3 includes mode and TOS fixed effects along with agency and time fixed effects.

Table 6 shows the results for the impact of COVID-19 safer-at-home policies on public transit ridership. As it can be seen, the estimate for the interaction term TREATEDSAFER is negative in all three columns. However, they are not statistically significant at conventional levels. This suggests that the implementation of safer-at-home policies did not cause a statistically significant decrease in ridership. Therefore, the fall in ridership across different modes of transports in US can be reasonably attributed to the pandemic as a whole rather than safer-at-home policies. Table 7 confirms these results for the dependent variable public transit vehicle usage in terms of hours travelled during service. The estimates for the interaction term TREATEDSAFER are negative and not statistically significant at conventional levels.

Table 8 shows the results for the impact of COVID-19 safer-at-home policies on public transit vehicle usage in terms of number of miles travelled during service. The estimates for the interaction term TREATEDSAFER are negative in all columns, but statistically significant at the 10 percent level solely in Column 2. The estimate suggests that the implementation of safer-at-home policies decreased average number of miles travelled by public transit vehicles during service by about 15 percent. After the inclusion of modal and TOS fixed effects in Column 3, the estimate for the interaction term becomes statistically insignificant at conventional levels. Therefore, after accounting for time-invariant characteristics of different modes and TOS across states, the implementation of safer-at-home policies did not cause a decrease in average number of miles travelled by public transit vehicles during service.

6 Conclusion

COVID-19 has had large impacts on health and to important changes in behavior of people. One of those changes is in the way people use public transport. This paper investigates the short term impact of COVID-19 and safer-at-home policies on public transit ridership and vehicle usage in the US. To the best of knowledge, this paper is the first to use the NTD database to answer this research question. This database contains monthly data on unlinked passenger trip (UPT), vehicle revenue hours (VRH) and vehicle revenue miles (VRM). To understand the impact of COVID-19, a pre/post regression is utilized. Moreover, using the variation in implementation of safer-at-home policies across states, this paper adopts a DID framework to identify the causal impact of lockdowns on public transit ridership and vehicle usage.

The pre/post results show that there has been a statistically significant drop in overall public transit ridership and vehicle usage after incidence of COVID-19. However, there is variation in ridership across different modes. The paper finds that smaller modes experienced greater decreases in ridership and vehicle usage. On the other hand, the 'demand driven' modes saw increase in ridership. The DID results show that the implementation of safer-at-home policies did lead to a larger decrease in public transit ridership and vehicle usage although the point estimates are not statistically significant at conventional levels. Therefore, the fall in ridership and vehicle usage can be mostly attributed to the pandemic as a whole rather than policies such as safer-at-home policies.

The findings of this paper are important from a policy perspective because of the significant financial and economic costs associated with US public transit. With continued proliferation of COVID-19 cases and deaths in the US, Americans might continue to engage in risk-averse behavior and avoid public transit for a prolonged period. This will lead to continuous decline in revenue and rise in costs (e.g., cleaning and purchase of protective equipment). Therefore, it is important to allocate resources in an efficient manner. As this paper points out, some of the 'demand-driven' modes saw increase in ridership. Transit agencies and authorities might engage more transit vehicles to cater to this latent demand from public transit users. Moreover, this paper shows that smaller modes experienced greater loss in ridership. Therefore, government subsidy allocation might consider the higher revenue losses for smaller transit agencies and appropriate government assistance in an equitable manner.

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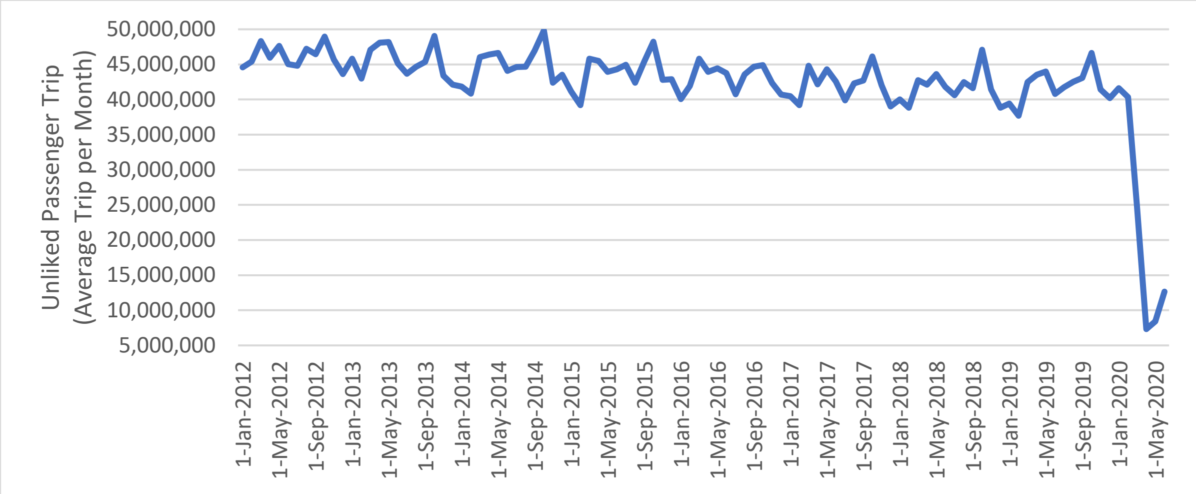
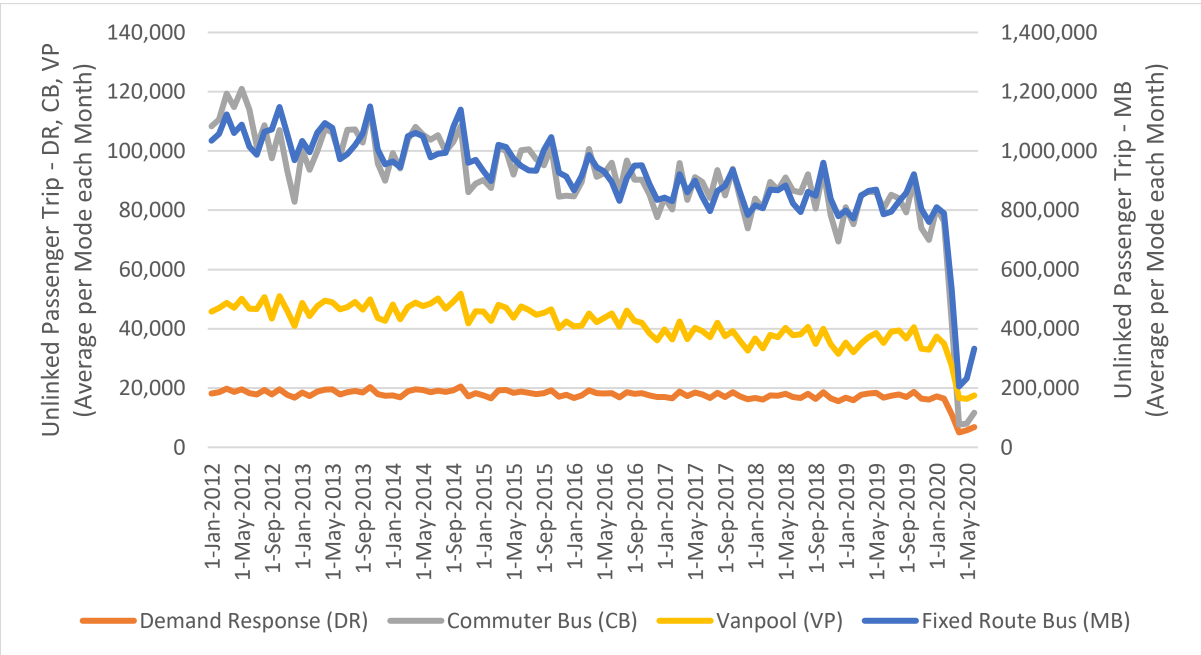
8 Figures

Figure 1: Unlinked Passenger Trip – Average Number of Trips per Month (January 2012 – June 2020)



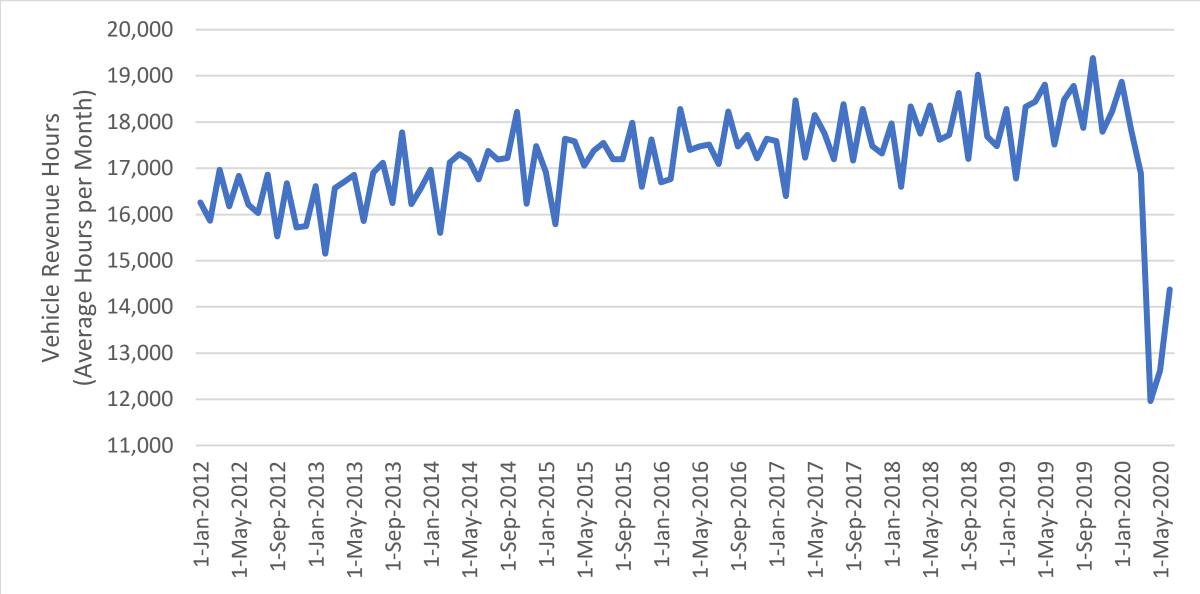
Note: This figure presents the impact of COVID-19 on public transit ridership. Unlinked Passenger Trip (UPT) is shown as average number of passengers riding on public transit across all modes each month. The time period is between January 2012 and June 2020.

Figure 2: Unlinked Passenger Trip – Average Number of Trips per Month for Top 4 modes of transport (January 2012 – June 2020)



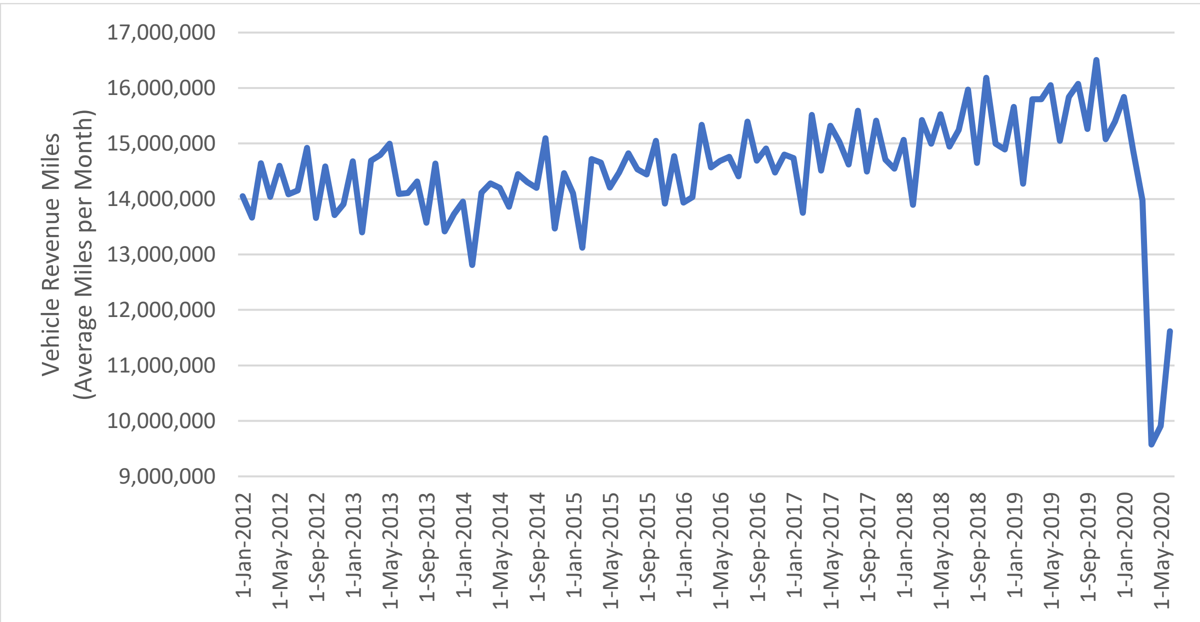
Note: The figure shows the effect of COVID-19 on public transit ridership for top four modes of transport. UPT in terms of average number of passengers each month for the top four modes of transit i.e. Commuter Bus (CB), Demand Response (DR), Fixed Route Bus (MB) and Vanpool (VP). The time period is between January 2012 and June 2020. The primary (left) axis shows UPT for CB, DR and VP. The secondary (right) axis shows UPT for MB.

Figure 3: Vehicle Revenue Hours – Average Number of Hours of Service per Month (January 2012 – June 2020)



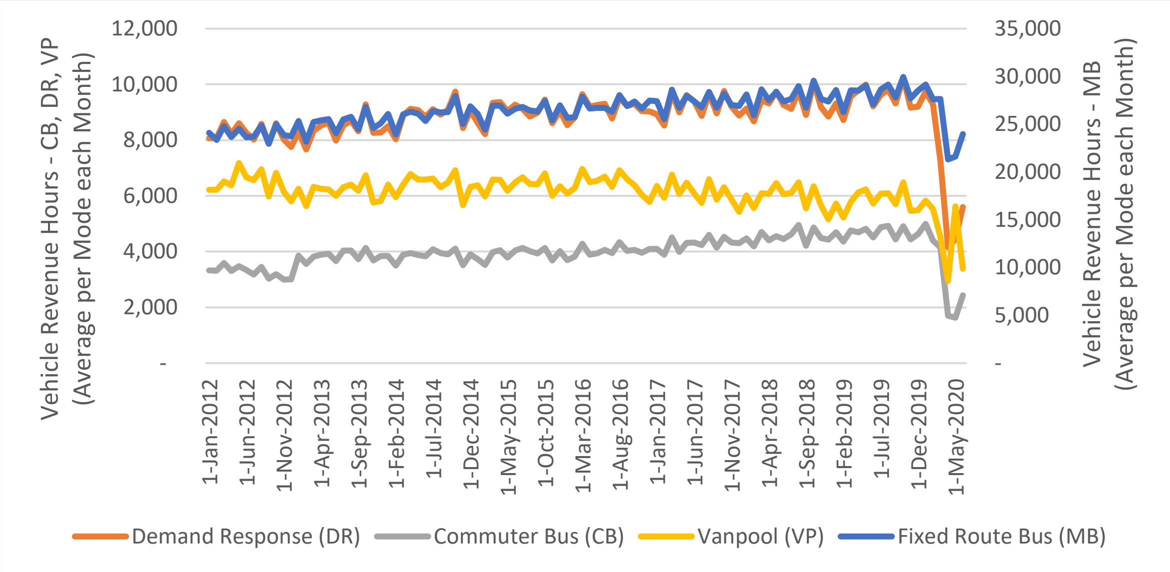
Note: This figure presents the impact of COVID-19 on public transit vehicle usage in terms of hours. Vehicle Revenue Hours (VRH) is shown as average number of hours public transit have been used during service for all modes each month. The time period is between January 2012 and June 2020.

Figure 4: Vehicle Revenue Miles – Average Number of Miles Travelled During Service per Month (January 2012 – June 2020)



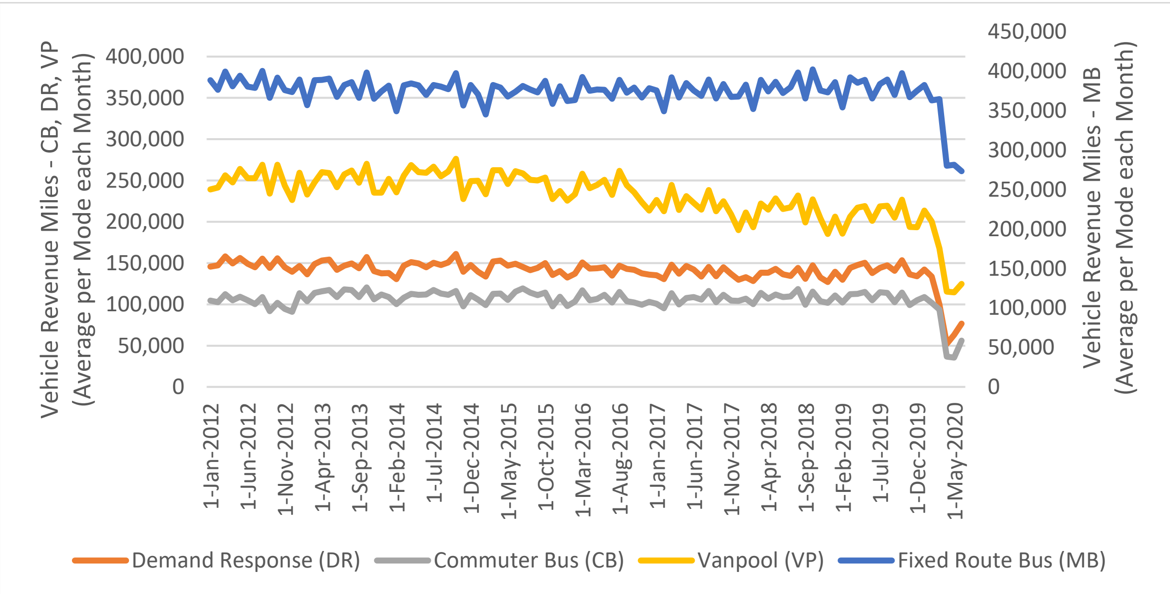
Note: This figure presents the impact of COVID-19 on public transit vehicle usage in terms of miles. Vehicle Revenue Miles (VRM) is shown as average number of miles public transit have been running during service for all modes each month. The time period is between January 2012 and June 2020.

Figure 5: Vehicle Revenue Hours – Average Number of Hours Travelled per Month for Top 4 modes of transport (January 2012 – June 2020)



Note: The figure shows the effect of COVID-19 on public transit vehicle usage. VRH is the average number of hours public transit have been in use during service each month for the top four modes of transit i.e. Commuter Bus (CB), Demand Response (DR), Fixed Route Bus (MB) and Vanpool (VP). The time period is between January 2012 and June 2020. The primary (left) axis shows VRH for CB, DR and VP. The secondary (right) axis shows VRH for MB.

Figure 6: Vehicle Revenue Miles – Average Number of Miles Travelled per Month for Top 4 modes of transport (January 2012 – June 2020)



Note: The figure shows the effect of COVID-19 on public transit vehicle usage. VRM is the average number of miles public transit have been running during service each month for the top four modes of transit i.e. Commuter Bus (CB), Demand Response (DR), Fixed Route Bus (MB) and Vanpool (VP). The time period is between January 2012 and June 2020. The primary (left) axis shows VRM for CB, DR and VP. The secondary (right) axis shows VRM for MB.

9 Tables

Table 1: US Safer-at-Home Policies – Dates for Start, Announcement, Expiry

State	(1) Date of Lockdown (Start)	(2) Announcement Date	(3) Date of Lockdown (Expiry)
Alabama	2020-04-04	2020-04-03	2020-04-30
Alaska	2020-03-28	2020-03-27	2020-04-24
Arizona	2020-03-31	2020-03-30	2020-05-15
Arkansas			
California	2020-03-19	2020-03-19	2020-05-25
Colorado	2020-03-26	2020-03-25	2020-04-26
Connecticut	2020-03-23	2020-03-20	2020-05-20
Delaware	2020-03-24	2020-03-22	2020-05-31
District of Columbia	2020-04-01	2020-03-30	2020-05-29
Florida	2020-04-03	2020-04-01	2020-05-04
Georgia	2020-04-03	2020-04-01	2020-04-30
Hawaii	2020-03-25	2020-03-23	2020-05-31
Idaho	2020-03-25	2020-03-25	2020-04-30
Illinois	2020-03-21	2020-03-20	2020-05-29
Indiana	2020-03-24	2020-03-23	2020-05-04
Iowa			
Kansas	2020-03-30	2020-03-28	2020-05-03
Kentucky	2020-03-26	2020-03-23	2020-05-20
Louisiana	2020-03-23	2020-03-22	2020-05-15
Maine	2020-04-02	2020-03-31	2020-05-31
Maryland	2020-03-30	2020-03-30	2020-05-15
Massachusetts	2020-03-24	2020-03-23	2020-05-18
Michigan	2020-03-24	2020-03-23	2020-06-01
Minnesota	2020-03-27	2020-03-26	2020-05-17
Mississippi	2020-04-03	2020-04-01	2020-04-27
Missouri	2020-04-06	2020-04-03	2020-05-03
Montana	2020-03-28	2020-03-26	2020-04-26
Nebraska			
Nevada	2020-04-01	2020-04-01	2020-05-09
New Hampshire	2020-03-27	2020-03-26	2020-06-15
New Jersey	2020-03-21	2020-03-21	2020-06-09
New Mexico	2020-03-23	2020-03-23	2020-05-31
New York	2020-03-22	2020-03-20	2020-05-28
North Carolina	2020-03-30	2020-03-27	2020-05-22
North Dakota			
Ohio	2020-03-23	2020-03-22	2020-05-29
Oklahoma			
Oregon	2020-03-23	2020-03-22	2020-05-15
Pennsylvania	2020-04-01	2020-03-23	2020-06-04
Rhode Island	2020-03-28	2020-03-28	2020-05-08

South Carolina	2020-04-07	2020-04-06	2020-05-04
South Dakota			
Tennessee	2020-03-31	2020-03-30	2020-04-30
Texas	2020-04-02	2020-03-31	2020-04-30
Utah			
Vermont	2020-03-25	2020-03-24	2020-05-15
Virginia	2020-03-30	2020-03-30	2020-06-10
Washington	2020-03-23	2020-03-23	2020-05-31
West Virginia	2020-03-24	2020-03-23	2020-05-03
Wisconsin	2020-03-25	2020-03-24	2020-05-13
Wyoming			

Note: The table presents dates related to safer-at-home policies for each of the states in US. The dates are from the New York Times. Column 1 shows the dates safer-at-home policies were implemented. Column 2 shows the dates that these policies were announced, which is usually 1 day prior to implementation. Column 3 shows the dates safer-at-home policies expired. The gaps in Columns 1, 2 and 3 reflect that the corresponding states did not implement safer-at-home policies.

Table 2: Summary Statistics for Transit Ridership and Vehicle Usage

	Count	Mean	Standard Deviation	Minimum	Maximum
Transit Ridership and Vehicle Usage Variables:					
UPT	121,551	679,244	6,802,250	1	254,902,384
VRH	114,846	18,973	69,932	1	1,690,628
VRM	114,846	283,046	1,080,694	11	30,830,497

Note: The data is from the National Transit Database. UPT is the number of passengers who board public transit vehicles. VRH is the number or hours that a public transit vehicle travels while in revenue service. VRM is the number of miles that a public transit vehicle travels while in revenue service. The number is for each mode used by different transit agencies across US for all months between January 2012 and June 2020. The final dataset dropped the entire mode for a specific transit agency if there is no data available post COVID-19 i.e. for March, April, May and June 2020. This is the reason for the variation in the number of observations between ridership (UPT) and vehicle usage (VRH and VRM).

Table 3: Impact of COVID-19 on Public Transit Ridership (UPT) – Pre/Post Regression

VARIABLES	(1) log UPT	(2) log UPT	(3) log UPT	(4) log UPT	(5) log UPT
POSTCOVID	-1.111***	-1.112***	-1.102***	-1.262***	-1.259***
	(0.020)	(0.020)	(0.032)	(0.142)	(0.142)
POSTCOVID X Mode = AR				-2.382***	-2.367***
				(0.142)	(0.147)
POSTCOVID X Mode = CB				-0.508***	-0.504***
				(0.171)	(0.171)
POSTCOVID X Mode = CC				0.230	0.245*
				(0.141)	(0.147)
POSTCOVID X Mode = CR				-0.738***	-0.735***
				(0.204)	(0.204)
POSTCOVID X Mode = DR				0.315**	0.321**
				(0.145)	(0.145)
POSTCOVID X Mode = DT				0.274	0.272
				(0.194)	(0.193)
POSTCOVID X Mode = FB				-0.302	-0.296
				(0.256)	(0.256)
POSTCOVID X Mode = HR				-0.513***	-0.498***
				(0.173)	(0.178)
POSTCOVID X Mode = IP				-0.659**	-0.643**
				(0.278)	(0.280)
POSTCOVID X Mode = LR				0.074	0.088
				(0.185)	(0.189)
POSTCOVID X Mode = MB				0.176	0.185
				(0.145)	(0.148)
POSTCOVID X Mode = MG				-1.252**	-1.244*
				(0.632)	(0.637)
POSTCOVID X Mode = PB				-2.028***	-2.031***
				(0.142)	(0.141)
POSTCOVID X Mode = RB				0.275	0.291
				(0.189)	(0.191)

POSTCOVID X Mode = SR				0.131	0.138
				(0.230)	(0.231)
POSTCOVID X Mode =TB				-0.012	0.003
				(0.317)	(0.320)
POSTCOVID X Mode = TR				-0.244*	-0.246*
				(0.143)	(0.142)
POSTCOVID X Mode = VP				0.340*	0.344*
				(0.187)	(0.187)
POSTCOVID X TOS = DO			-0.020		-0.018
			(0.045)		(0.047)
Constant	10.444***	9.643***	9.643***	9.644***	9.643***
	(0.016)	(0.103)	(0.103)	(0.103)	(0.103)
Observations	121,551	121,551	121,551	121,551	121,551
R-squared	0.893	0.914	0.914	0.914	0.914
Modes FE	No	Yes	Yes	Yes	Yes
TOS FE	No	Yes	Yes	Yes	Yes
Agency FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Note: The impact of COVID-19 on public transit ridership. The dependent variable is the log of UPT at the transit agency level. POSTCOVID is a dummy variable equal to 1 if the months are equal to March, April, May and June 2020 and 0 otherwise. Column 1 does not include Mode and Type of Service (TOS) fixed effects, while Columns 2 to 5 include them. Columns 3 and 5 include the interaction term between POSTCOVID and TOS = Directly Operated (DO). Columns 4 and 5 include the interaction term between POSTCOVID and 18 different modes of public transit. The modes include: AR = Alaska Railroad, CB = Commuter Bus, CC = Cable Car, CR = Commuter Rail, , DR = Demand Response, DT = Demand Taxi, FB = Ferry Boat, HR = Heavy Rail, IP = Inclined Plane, LR = Light Rail, MB = Fixed Route bus. MG = Monorail/Automated Guideway, PB = Publico, RB = Bus Rapid Transit, SR = Streetcar, TB = Trolleybus, TR = Aerial Tramway, VP = Vanpool. The interaction term between POST COVID and the remaining mode YR = Hybrid Rail drops out of the regression to avoid multi-collinearity. All columns include agency and time (month and year) fixed effects. The standard errors are reported in parentheses and are clustered at the transit agency level. (*** p<0.01, ** p<0.05, * p<0.1).

Table 4: Impact of COVID-19 on Public Transit Vehicle Usage (VRH) – Pre/Post Regression

VARIABLES	(1) log VRH	(2) log VRH	(3) log VRH	(4) log VRH	(5) log VRH
POSTCOVID	-0.563***	-0.561***	-0.595***	-0.166	-0.158
	(0.015)	(0.015)	(0.025)	(0.116)	(0.119)
POSTCOVID X Mode = AR				-2.649***	-2.601***
				(0.117)	(0.123)
POSTCOVID X Mode = CB				-0.540***	-0.529***
				(0.152)	(0.153)
POSTCOVID X Mode = CC				-0.218*	-0.170
				(0.117)	(0.124)
POSTCOVID X Mode = CR				-0.286*	-0.276*
				(0.152)	(0.153)
POSTCOVID X Mode = DR				-0.537***	-0.519***
				(0.119)	(0.122)
POSTCOVID X Mode = DT				-0.950***	-0.958***
				(0.172)	(0.174)
POSTCOVID X Mode = FB				-0.493***	-0.473***
				(0.158)	(0.159)
POSTCOVID X Mode = HR				-0.250	-0.203
				(0.166)	(0.170)
POSTCOVID X Mode = IP				-0.967**	-0.920**
				(0.436)	(0.436)
POSTCOVID X Mode = LR				-0.090	-0.048
				(0.146)	(0.151)
POSTCOVID X Mode = MB				-0.172	-0.147
				(0.120)	(0.124)
POSTCOVID X Mode = MG				-0.604*	-0.584*
				(0.324)	(0.323)
POSTCOVID X Mode = PB				-2.935***	-2.943***
				(0.117)	(0.120)
POSTCOVID X Mode = RB				0.083	0.130
				(0.140)	(0.144)

POSTCOVID X Mode = SR				0.006	0.027
				(0.151)	(0.155)
POSTCOVID X Mode =TB				-0.434**	-0.387*
				(0.220)	(0.223)
POSTCOVID X Mode = TR				0.089	0.081
				(0.118)	(0.120)
POSTCOVID X Mode = VP				-0.526***	-0.514***
				(0.147)	(0.149)
POSTCOVID X TOS = DO			0.069*		-0.056
			(0.038)		(0.038)
Constant	8.333***	7.756***	7.757***	7.756***	7.754***
	(0.015)	(0.088)	(0.088)	(0.088)	(0.088)
Observations	114,846	114,846	114,846	114,846	114,846
R-squared	0.851	0.874	0.874	0.874	0.874
Modes FE	No	Yes	Yes	Yes	Yes
TOS FE	No	Yes	Yes	Yes	Yes
Agency FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Note: The impact of COVID-19 on public transit vehicle usage. The dependent variable is the log of VRH at the transit agency level. POSTCOVID is a dummy variable equal to 1 if the months are equal to March, April, May and June 2020 and 0 otherwise. Column 1 does not include Mode and Type of Service (TOS) fixed effects, while Columns 2 to 5 include them. Columns 3 and 5 include the interaction term between POSTCOVID and TOS = Directly Operated (DO). Columns 4 and 5 include the interaction term between POSTCOVID and 18 different modes of public transit. The modes include: AR = Alaska Railroad, CB = Commuter Bus, CC = Cable Car, CR = Commuter Rail, , DR = Demand Response, DT = Demand Taxi, FB = Ferry Boat, HR = Heavy Rail, IP = Inclined Plane, LR = Light Rail, MB = Fixed Route bus. MG = Monorail/Automated Guideway, PB = Publico, RB = Bus Rapid Transit, SR = Streetcar, TB = Trolleybus, TR = Aerial Tramway, VP = Vanpool. The interaction term between POST COVID and the remaining mode YR = Hybrid Rail drops out of the regression to avoid multi-collinearity. All columns include agency and time (month and year) fixed effects. The standard errors are reported in parentheses and are clustered at the transit agency level. (*** p<0.01, ** p<0.05, * p<0.1).

Table 5: Impact of COVID-19 on Public Transit Vehicle Usage (VRM) – Pre/Post Regression

VARIABLES	(1) log VRM	(2) log VRM	(3) log VRM	(4) log VRM	(5) log VRM
POSTCOVID	-0.613***	-0.611***	-0.647***	-0.232**	-0.223*
	(0.015)	(0.015)	(0.025)	(0.118)	(0.118)
POSTCOVID X Mode = AR				-2.610***	-2.561***
				(0.119)	(0.123)
POSTCOVID X Mode = CB				-0.484***	-0.472***
				(0.153)	(0.153)
POSTCOVID X Mode = CC				-0.658***	-0.610***
				(0.119)	(0.123)
POSTCOVID X Mode = CR				-0.263*	-0.253*
				(0.143)	(0.143)
POSTCOVID X Mode = DR				-0.589***	-0.572***
				(0.121)	(0.122)
POSTCOVID X Mode = DT				-0.866***	-0.874***
				(0.172)	(0.173)
POSTCOVID X Mode = FB				-0.400**	-0.379**
				(0.188)	(0.187)
POSTCOVID X Mode = HR				-0.214	-0.167
				(0.164)	(0.167)
POSTCOVID X Mode = IP				-0.750***	-0.702***
				(0.253)	(0.253)
POSTCOVID X Mode = LR				-0.081	-0.038
				(0.150)	(0.153)
POSTCOVID X Mode = MB				-0.114	-0.088
				(0.121)	(0.123)
POSTCOVID X Mode = MG				-0.771**	-0.751**
				(0.302)	(0.310)
POSTCOVID X Mode = PB				-2.532***	-2.540***
				(0.119)	(0.119)
POSTCOVID X Mode = RB				0.151	0.199
				(0.146)	(0.149)

POSTCOVID X Mode = SR				0.080	0.100
				(0.147)	(0.149)
POSTCOVID X Mode =TB				-0.370	-0.322
				(0.228)	(0.231)
POSTCOVID X Mode = TR				0.100	0.092
				(0.119)	(0.120)
POSTCOVID X Mode = VP				-0.517***	-0.504***
				(0.147)	(0.148)
POSTCOVID X TOS = DO			0.072*		-0.057
			(0.039)		(0.039)
Constant	11.072***	10.520***	10.521***	10.519***	10.518***
	(0.015)	(0.087)	(0.087)	(0.087)	(0.087)
Observations	114,846	114,846	114,846	114,846	114,846
R-squared	0.857	0.877	0.877	0.877	0.877
Modes FE	No	Yes	Yes	Yes	Yes
TOS FE	No	Yes	Yes	Yes	Yes
Agency FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Note: The impact of COVID-19 on public transit vehicle usage. The dependent variable is the log of VRM at the transit agency level. POSTCOVID is a dummy variable equal to 1 if the months are equal to March, April, May and June 2020 and 0 otherwise. Column 1 does not include Mode and Type of Service (TOS) fixed effects, while Column 2 to 5 include them. Columns 3 and 5 include the interaction term between POSTCOVID and TOS = Directly Operated (DO). Columns 4 and 5 include the interaction term between POSTCOVID and 18 different modes of public transit. The modes include: AR = Alaska Railroad, CB = Commuter Bus, CC = Cable Car, CR = Commuter Rail, , DR = Demand Response, DT = Demand Taxi, FB = Ferry Boat, HR = Heavy Rail, IP = Inclined Plane, LR = Light Rail, MB = Fixed Route bus. MG = Monorail/Automated Guideway, PB = Publico, RB = Bus Rapid Transit, SR = Streetcar, TB = Trolleybus, TR = Aerial Tramway, VP = Vanpool. The interaction term between POST COVID and the remaining mode YR = Hybrid Rail drops out of the regression to avoid multi-collinearity. All columns include agency and time (month and year) fixed effects. The standard errors are reported in parentheses and are clustered at the transit agency level. (*** p<0.01, ** p<0.05, * p<0.1).

Table 6: Impact of Safer-at-Home Policies on Public Transit Ridership (UPT) – DID

VARIABLES	(1) Log UPT	(2) log UPT	(3) log UPT
POSTSAFER	-0.956***	-0.980***	-1.021***
	(0.214)	(0.135)	(0.142)
TREATEDSAFER	-0.172	-0.192	-0.151
	(0.220)	(0.143)	(0.151)
Constant	10.166***	10.463***	9.663***
	(0.292)	(0.016)	(0.098)
Observations	121,551	121,551	121,551
R-squared	0.513	0.8938	0.9135
Modes FE	No	No	Yes
TOS FE	No	No	Yes
Agency FE	No	Yes	Yes
Month FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Note: The impact of COVID-19 safer-at-home policies on US public transit ridership. For all columns, the dependent variable is the log of UPT. POSTSAFER is a dummy variable equal to 1 if the months are equal to April, May and June 2020 and 0 otherwise. TREATEDSAFER is the interaction term between treated group (i.e. US states which implemented safer-at-home policies) and the POSTSAFER dummy variable. Columns 1 does not include Agency, Mode and Type of Service (TOS) fixed effects. Column 2 includes Agency fixed effects. Column 3 includes Agency, Mode and TOS fixed effects. All columns include agency and time (month and year) fixed effects. The standard errors are reported in parentheses and are clustered at the state level. (*** p<0.01, ** p<0.05, * p<0.1).

Table 7: Impact of Safer-at-Home Policies on Public Transit Vehicle Usage (VRH) – DID

VARIABLES	(1) log VRH	(2) log VRH	(3) log VRH
POSTSAFER	-0.405**	-0.437***	-0.471***
	(0.153)	(0.107)	(0.106)
TREATED SAFER	-0.130	-0.173	-0.135
	(0.152)	(0.109)	(0.108)
Constant	8.070***	8.343***	7.765***
	(0.293)	(0.013)	(0.085)
Observations	114,846	114,846	114,846
R-squared	0.406	0.851	0.874
Modes FE	No	No	Yes
TOS FE	No	No	Yes
Agency FE	No	Yes	Yes
Month FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Note: The impact of COVID-19 safer-at-home policies on US public transit vehicle usage in terms of hours during service. For Columns 3 and 4, the dependent variable is the log of VRH. POSTSAFER is a dummy variable equal to 1 if the months are equal to April, May and June 2020 and 0 otherwise. TREATEDSAFER is the interaction term between treated group (i.e. US states which implemented safer-at-home policies) and the POSTSAFER dummy variable. Columns 1 does not include Agency, Mode and Type of Service (TOS) fixed effects. Column 2 includes Agency fixed effects. Column 3 includes Agency, Mode and TOS fixed effects. All columns include agency and time (month and year) fixed effects. The standard errors are reported in parentheses and are clustered at the state level. (*** p<0.01, ** p<0.05, * p<0.1).

Table 8: Impact of Safer-at-Home Policies on Public Transit Vehicle Usage (VRM) – DID

VARIABLES	(1) log VRM	(2) log VRM	(3) log VRM
POSTSAFER	-0.488***	-0.490***	-0.523***
	(0.145)	(0.096)	(0.097)
TREATED SAFER	-0.095	-0.169*	-0.134
	(0.144)	(0.098)	(0.100)
Constant	10.742***	11.083***	10.530***
	(0.358)	(0.013)	(0.084)
Observations	114,846	114,846	114,846
R-squared	0.507	0.857	0.877
Modes FE	No	No	Yes
TOS FE	No	No	Yes
Agency FE	No	Yes	Yes
Month FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Note: The impact of COVID-19 safer-at-home policies on US public transit vehicle usage in terms of miles travelled during service. For Columns 3 and 4, the dependent variable is the log of VRM. POSTSAFER is a dummy variable equal to 1 if the months are equal to April, May and June 2020 and 0 otherwise. TREATEDSAFER is the interaction term between treated group (i.e. US states which implemented safer-at-home policies) and the POSTSAFER dummy variable. Columns 1 does not include Agency, Mode and Type of Service (TOS) fixed effects. Column 2 includes Agency fixed effects. Column 3 includes Agency, Mode and TOS fixed effects. All columns include agency and time (month and year) fixed effects. The standard errors are reported in parentheses and are clustered at the state level. (*** p<0.01, ** p<0.05, * p<0.1).